CROP AND ENERGY PRICE LINKS SINCE 2006:
AN ANLYSIS OF A BIOFUEL POLICY FRAMEWORK

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ABSTRACT

High world food prices after 2006 concerned governments across the globe. Among various contributing factors, biofuels have received wide attention in recent years with more and more studies analyzing the implication of biofuel policies on global food supply and demand conditions. Relying on a model based upon U.S. biofuel policies, this paper studies the price links between crop and energy commodities induced by biofuel production, and simulates commodity price changes due to market and policy shifts. Results suggest price links exist between crop and energy commodities but more accurate measurement of commodity price changes induced by different market conditions will require the construction of a more detailed structural model.

BIOGRAPHICAL SKETCH

Born in a water town in east China, Bingyi Yan grew up with family members who shared passion for literature, music, and arts. He first exposed himself to western culture when he attended high school at Raffles Institution in Singapore and later decided to come to the United States to broaden his horizon. At the University of Iowa, Bingyi studied economics, journalism, and creative non-fiction writing while he developed his interest in history and classics. Within his stay at Cornell, he explored different libraries besides his main occupation.

In his free time, Bingyi enjoys reading, writing, drawing, swimming, cooking, and playing the piano and harmonica. After graduating from Cornell with a degree in Applied Economics and Management, Bingyi will start a career in the United States as he continues the search for the meaning of his life.

In Memory of My Grandmother,

Shiyun Wu

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I would also like to thank the classmates and friends surrounding me who have given me both feedbacks on my work and help in my life in the past two years. It has been a blessing to live with a pair of lively roommates: Jason Troendle and Justin (Qingrun) Meng. Living close to Deyu Rao and Yan Li has also been great with their deep knowledge of econometrics programming languages and time-series data analysis. And thank you for your companionship, Whisky.

Lastly, to those faithful families who have always been on my side, I really appreciate everything you have done for me. Without all of you, I would not have had the chance to embark on this journey in an attempt to become something greater than myself.

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CHAPTER 1

INTRODUCTION

The 2007-08 world food price crisis caught most governments off guard. Within a few months after the second half of 2007, all grain and oilseed prices tripled (de Gorter, Drabik, and Just, 2015). Widespread riots and protests ensued in Asian and African countries as citizens demanded access to basic food. Meanwhile, though the United States was going through the Great Recession, high food prices did not spare the domestic market.

The phenomena perplexed economists. At first, researchers listed a plethora of factors that could have contributed to the crisis: nations' lax monetary policies, fiscal expansions of countries, weak US dollars, high oil prices, decreasing stocks, financial speculation, and natural disasters among many other explanations (Baffes and Haniotis, 2010; Heady and Fan, 2008). The traditional supply and demand framework still seemed to rule as food prices took a dive in 2009 and reamined low in 2010. Everything appeared to be just the product of another boom and bust business cycle with mean reversion until food prices started a new round of increase in 2011. While rice and wheat prices did not beat their record levels in 2008, corn and soybean prices reached new highs. Confusion spread and governors across the world demanded better explanation as economists ventured into new directions.

One sector that attracted wide attention was the biofuel industry. First originated from the Energy Policy Act of 2005, the Renewable Fuel Standard requires the blending of a minimum volume of renewable energy into transportation fuels in the United States each year. Among the miscellaneous products blenders can use to meet the annual blend goals, corn ethanol and soybean biodiesel stand out as two products that are both easier to produce and market.

Beginning in 2005, corn ethanol production capacity quickly expanded, starting from less than 4 billion gallons per year to over 14 billion gallons per year in 2011 (EIA, 2017). Meanwhile, biodiesel production also increased from 90.7 million gallons in 2005 to 967.5 million gallons in 2011 (EIA, 2017). Biofuel production expansion naturally drew stocks from the corn and soybean markets. With stable domestic crop production levels between 2005 and 2011, biofuels' share had been increasing over time. This new relationship between crop and energy led to the questioning of possible price links established.

Contrary to some of the other investigations that often model the new source of crop demand from biofuels as a rightward shift in the crop demand curve, we use the economic framework developed by de Gorter, Drabik, and Just (2015) that pays close attention to the deeper meaning of the implication of biofuel policies to study the price links between crop and energy. In Chapter 2, we will discuss the price relationships between crop and energy before and after the enactment of the Renewable Fuel Standard, what other researchers have done for the field, and the economic analysis framework we will develop and use. In Chapter 3, we will use both time-series econometric analysis and reduced-form models based on the theory framework in Chapter 2 to investigate the price relationships between different crop and energy commodities. In Chapter 4, we will explore the implication of different market and policy change scenarios to the crop and energy markets. Lastly, we will sum up our findings and make recommendations for future research in Chapter 5.

CHAPTER 2

ECONOMIC THEORIES OF ENERGY AND CROP PRICE LINKS

The interaction between the crop and energy markets has received wide attention after the implementation of the 2005 Renewable Fuel Standard (RFS) and the occurrence of the 2007 global food crisis. This chapter will discuss the linkages between the two markets with and without the RFS and then we will introduce an analysis framework based on biofuel policies. The economic theories in this chapter will guide the development of the empirical models in Chapter 3.

2.1 The Energy and Crop Price Links before the Biofuel Era

After the first gasoline-motored tractor appeared in 1892, crop production in the U.S. has gradually evolved into an energy intensive process with agricultural modernization in machinery, fertilizer, and chemicals (Janick, 2008). This process has continued in the biofuel era.

Before the great expansion in the production of biofuel in 2006, oil and energy prices used to influence crop prices through the channels of production and marketing (Baffes, 2007). Farming machines used in crop production are mostly fuel-based (direct energy usage) and the manufacturing of fertilizers and chemicals require fuels (indirect energy usage). Using the two most common Midwestern agricultural commodities (both energy-intensive) as examples, Figure 2.1.1 shows the cost ratios of energy (both direct and indirect) in the production of corn and soybean across the United States in recent years. In general, energy accounts for more than 40% and 50% of the operating cost of soybean and corn respectively. The costs of fertilizer, chemicals, and fuel, lube, and electricity each made up 41.14%, 8.37%, and 6.38% of the total operating cost of corn, and 20.04%, 16.15%, and 8.24% of the total operating cost of soybean in 2015 respectively (ERS, USDA, 2017). For the marketing channel, transportation cost of farm products with trucks and trains also adds to a significant portion of the retail price consumers pay for food. Depending on the weight and value ratio, perishability, and consumers' taste, the marketing margin of a crop can be very large.

We now examine the crop and energy price link before 2006. As shown in Figure 2.1.2, a quick inspection of the prices of corn and ethanol does not suggest the two commodities have a strong link prior to the beginning of the mass production of biofuels in 2006. Meanwhile, as the crude oil price started to increase in 2004, corn price followed its upward trend through input transmission in the energy and crop link (Baffes and Haniotis, 2010).

This crop and energy price relationship through the input channel held before 2006.

2.2 The Beginning of the Biofuel Era

Biofuels are biomass-based transportation fuels, including ethanol and biodiesel, that are often "blended with petroleum fuels" to be sold at gas stations (EIA, 2017). Due to the multiple goals biofuel policies aim to achieve, such as emission reduction, energy independence, and increasing famers' income, policies sourced in environmental, energy, agricultural, and international trade goals all can influence the biofuel industry (de Gorter, Drabik, and Just, 2015). Since the beginning of the mass production of biofuels in the U.S. in 2006, there have been major changes in the patterns of crop and fuel production along with the industry's expansion. This section will highlight the key policies and phenomena that have been parts of the rise of biofuel.

As the main purpose of this thesis is to examine the links between crops and energy, we will focus on those key policies that have induced the links. In particular, we will explain how

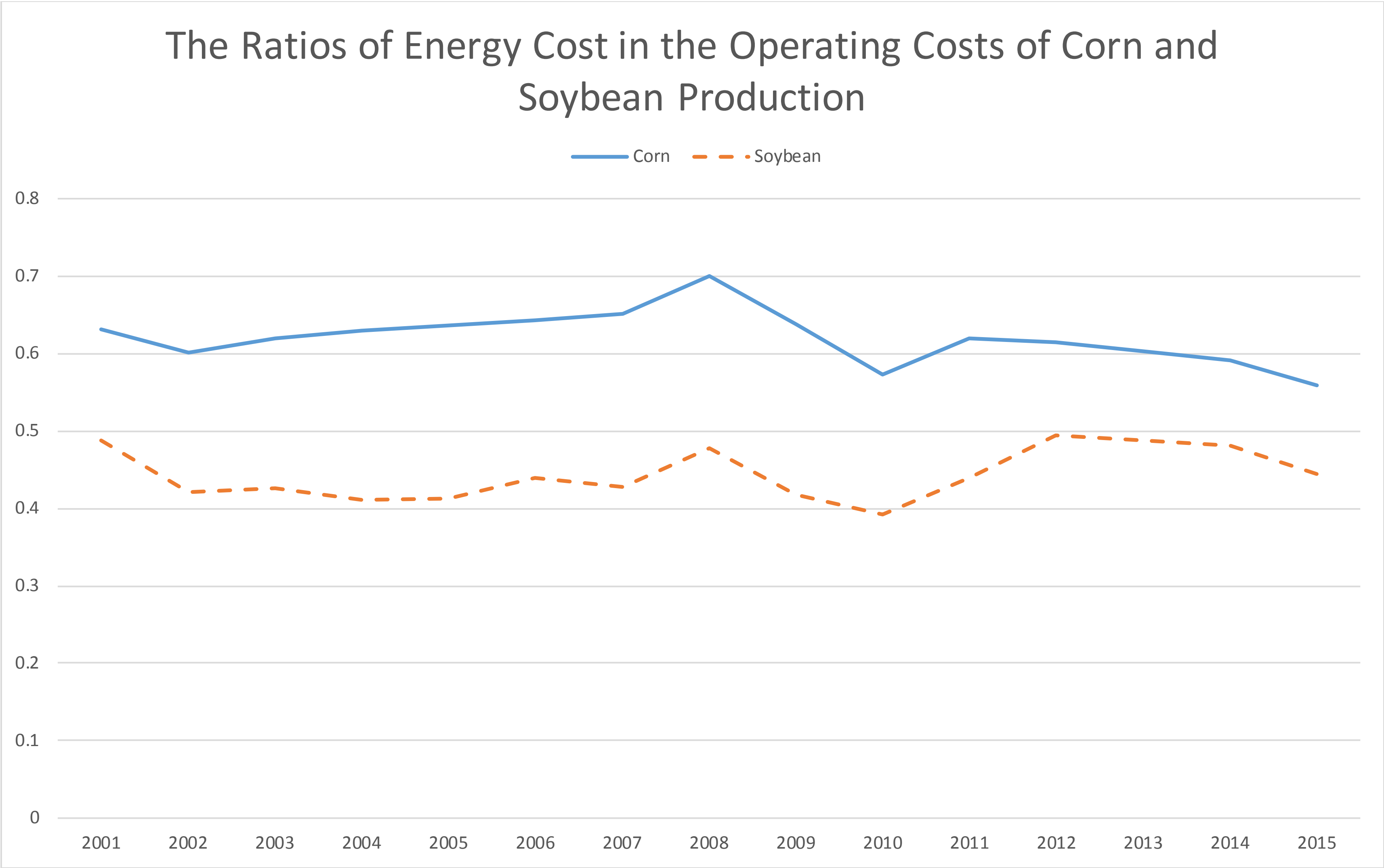

Figure 2.1.1 Energy Costs as Ratios of Corn and Soybean Production Operating Cost

Source: Commodity Costs and Returns, Economic Research Service, United States Department of Agriculture

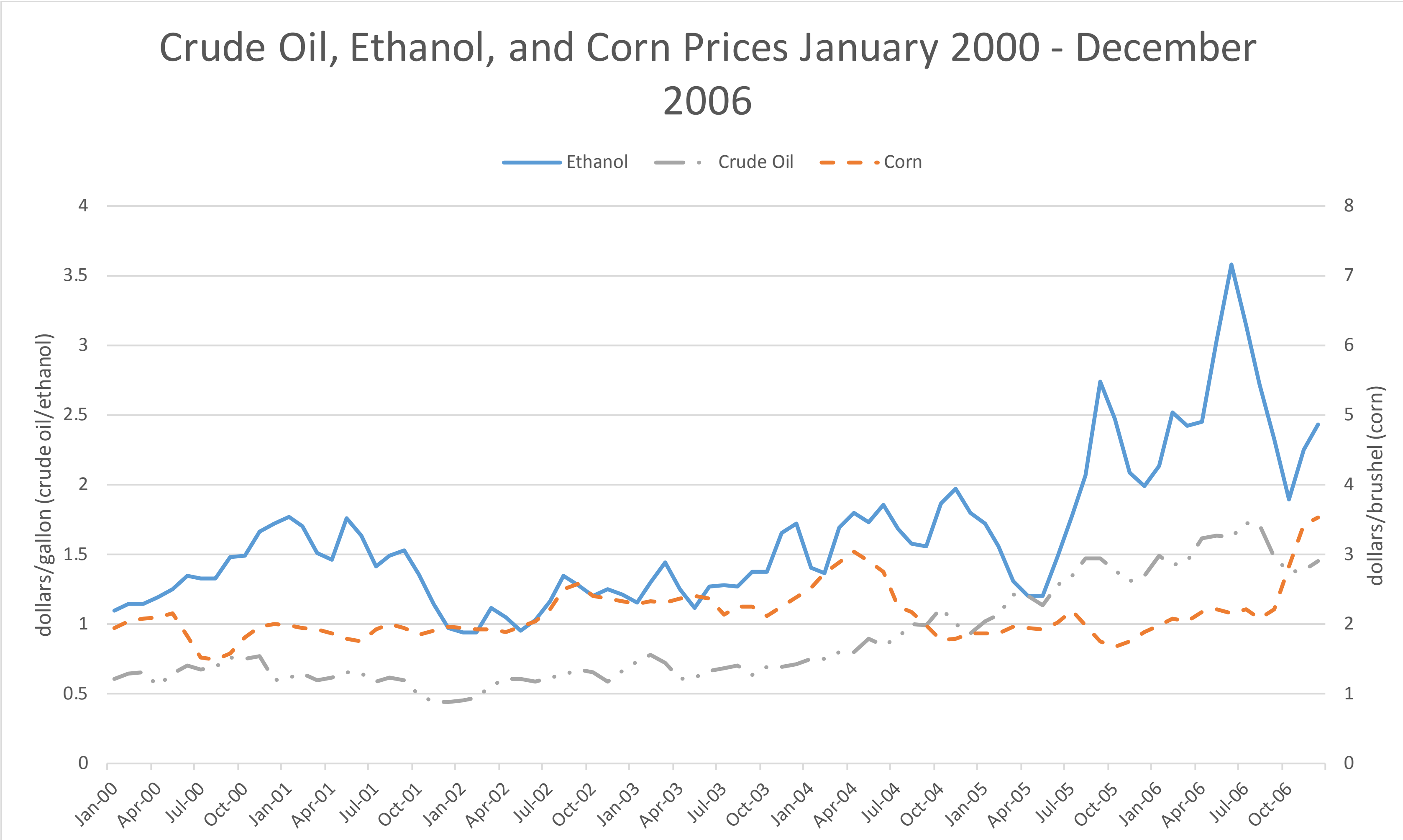

Figure 2.1.2 Crude Oil, Ethanol, and Corn Prices January 2000 – December 2006

Source: Ethanol and Unleaded Gasoline Average Rack Prices, Nebraska Government

Feed Grains Database, USDA, Economic Research Service

Commodity Markets, the World Bank

the ban of MTBE, an oxygenate for gasoline, and the federal legislations passed in the early 2000s have contributed towards the growth in the biofuel industry (de Gorter, Drabik, and Just, 2015).

In the early 1920s, gasoline producers blended tetraethyl lead into gasoline to reduce engine knocking, unwanted combustions of pockets of air and fuel mixture outside the designated engine chamber area that could lead to engine failures (British Medical Journal, 1928). However, due to concerns of lead poisoning through car exhaust, the US Congress and EPA together pushed the enforcement of the Clean Air Act first introduced in 1970, banning tetraethyl lead as an additive and substituting it with either MTBE or ethanol as an oxygenate that also boosts gasoline's octane level (EPA, 2017). However, the highly water-soluble MTBE from leaking underground storage tanks (LUST) was soon found in underground water and states banned its use in the early 2000s due to its nature as a potential carcinogen, leaving ethanol as the only viable alternative to boost octane number (Squillace, Pope, and Price, 1995).

Meanwhile, crude oil price continued to increase in the early 2000s, and the domestic biofuel industry had been developing since the 1980s with programs including the Small Ethanol Producer Tax Credit, reaching a production capacity of 1.8 billion gallons and using 7% of U.S. corn crops in 2001 (Schnepf, 2010). The federal Renewable Fuel Standard (RFS) of 2005, later expanded in 2007, became effective and mandated the consumption of 13.95 billion gallons of renewable fuel in 2011 (almost seven times more than the industry's total capacity in 2001) and the blending of ethanol into gasoline (EPA, 2017). Though RFS did not offer any direct tax credit or subsidy for the biofuel industry, its existence created a guaranteed market and raised biofuel products' prices compared to their levels without the mandate (Schnepf and Yacobucci, 2013).

The production of biofuel has taken off ever since with both government and industry's efforts and technology advancement in car engines. Figure 2.2.1 shows the expansion of the ethanol production capacity over the past decade under the EPA's RFS. As of 2015, ethanol's production capacity reached 15.5 billion gallons, consisting of 75.6% of EPA's 20.5 billion renewable consumption goal that year if all plants produced at full capacities (Nebraska Government, 2017). In November 2015, the Obama Administration ordered the blending of 14.5 billion gallons of ethanol into gasoline in 2016, making up more than 10% of US gasoline sold at pumps (Parker, 2015). Oil companies have warned about going above the E10 blend wall (having more than 10% of ethanol in the gasoline mixture) would potentially cause damage to car engines (de Gorter, Drabik, and Just, 2015). However, E15 is now available in 28 states and EPA approved its usage in cars manufactured in 2001 and later, which now make up more than 80% of the cars on the road (Renewable Fuel Association, 2015). Nevertheless, the annual blend goals of EPA's current RFS is very likely to restrict the further expansion in the production of traditional biofuel (like ethanol) with its conventional biofuel blend cap maxed out at 15 billion gallons per year from 2015 onward (EPA, 2017).

Meanwhile, expansion in biofuel production in the past decade has also led to major changes in corn usage. Table 2.2.1 shows the increasing share of ethanol production from corn production. Though this ratio is unlikely to increase due to the blend cap of RFS, it consists a major portion of total corn usage. Despite the diversion of ethanol production, however, U.S. remains the world's largest corn exporter, contributing 39.8% of the total corn traded in 2016 (FAS, USDA, 2017).

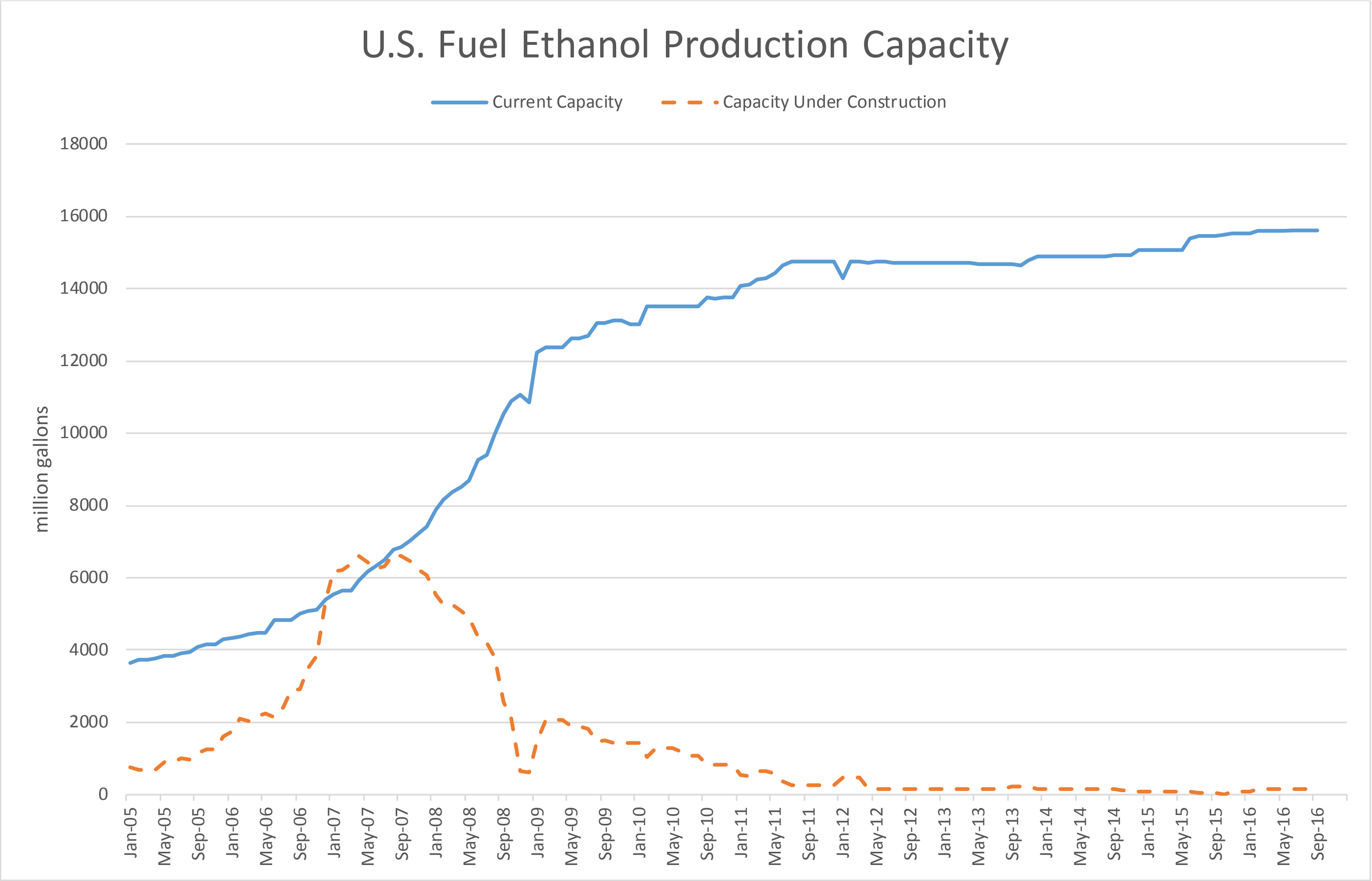

Figure 2.2.1 U.S. Fuel Ethanol Production Capacity in Million Gallons by Month

Source: Ethanol Production Capacity by Plant, Nebraska Government

Table 2.2.1 Corn Production and Ethanol Usage in the United States

	Corn Production (million bushels)	Ethanol and DDG Related Corn Usage (million bushels)	Ethanol and DDG Corn Usage Percentage (%)
2006	10,531	2,119	20.12
2007	13,038	3,049	23.39
2008	12,092	3,709	30.67
2009	13,092	4,591	35.07
2010	12,447	5,019	40.32
2011	12,360	5,000	40.45
2012	10,755	4,641	43.15
2013	13,899	5,123	36.86
2014	14,216	5,208	36.63
2015	13,601	5,206	38.28
2016	15,148	5,325	35.15

Source: USDA, NASS, Crop Production 2016 Summary / USDA, ERS Feed Outlook Jan. 17, 17

Biodiesel production has also increased since 2006 as shown in Figure 2.2.2. Compared to the more stable ethanol production growth, the government's tax credit (consumption subsidy) for biodiesel, an important factor to make its production viable, has not been very consistent since 2006. The one dollar production subsidy elapsed in 2010, 2012, and 2015 respectively, creating great uncertainties for the industry in those years. Table 2.2.2 reflects the soybeans used as feedstock for biodiesel productions in the past few years.

Table 2.2.2 Soybean Production and Biodiesel Usage in the United States

	Soybean Production (Million Bushels)	Biodiesel Related Soybean Usage (Million Bushels)	Biodiesel Soybean Usage Percentage (%)
2011	3,094	404	13.06
2012	3,042	400	13.15
2013	3,358	428	12.75
2014	3,927	442	11.26
2015	3,981	478	12.01

Source: Biodiesel Usage, Projections & Soybean Balance Sheet, Wisner, 2015

2.3 Literature on the Crop and Energy Price Links

With biofuel production stepping up and crop usage volume expanding in the late 2000s, the impact of biofuel policies on food prices has attracted wide attention. Researchers have

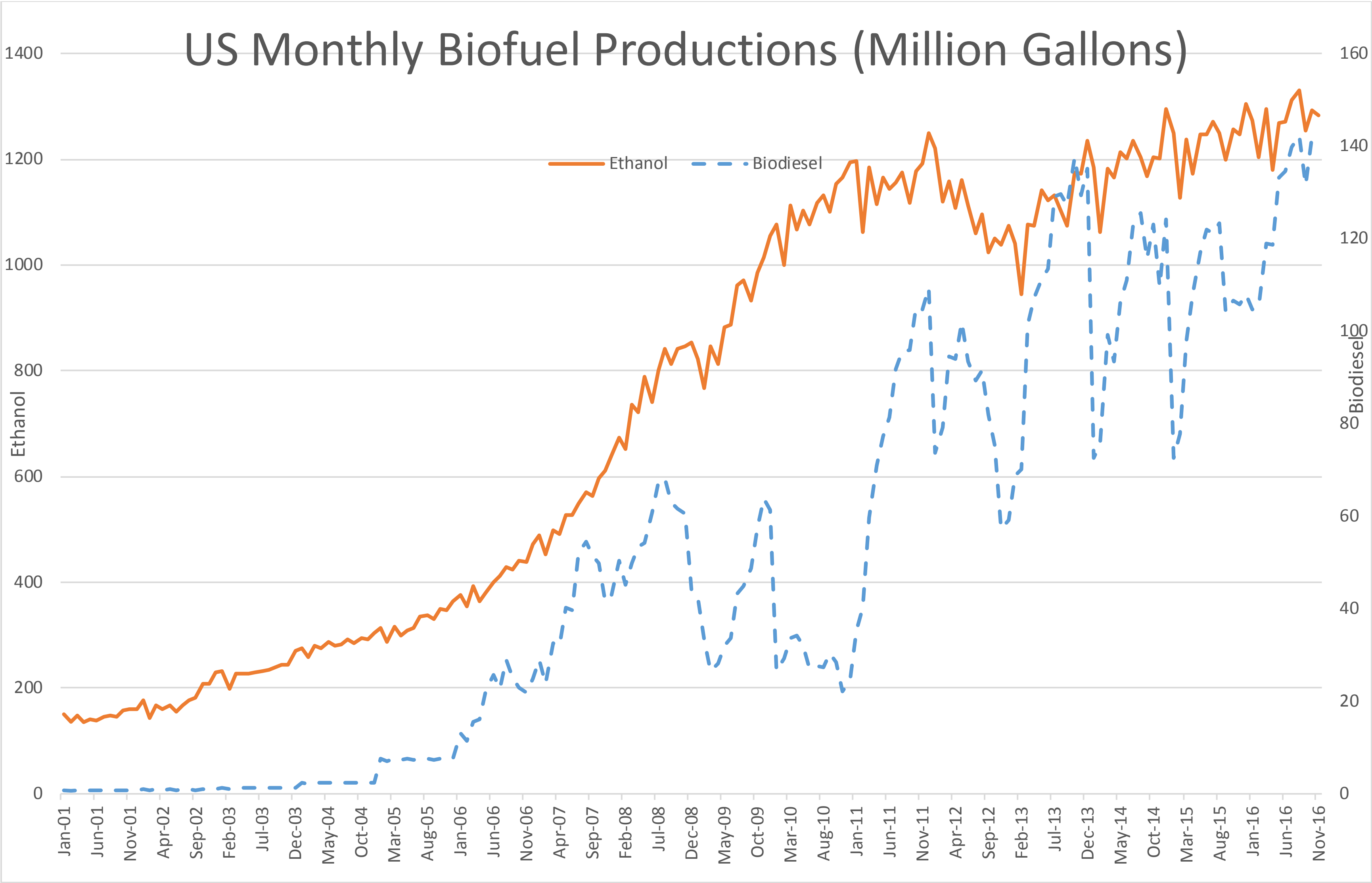

Figure 2.2.2 US Monthly Biofuel Production in Million Gallons

Source: EIA Monthly Energy Review, Table 10.3 & 10.4

suggested numerous economic theory models and econometric techniques to study the subject, but results do not always agree with each other as the relative young body of literature continues to evolve.

We begin our discussion with the pioneering research in the early years of large-scale biofuel production after the enactment of the 2005 Renewable Fuel Standard (RFS) and the global food crisis between 2007 and 2008. Headey and Fan (2008) suggested oil prices, USD exchange rates, crop demand from biofuel, and other commodity specific characteristics were important factors behind the 2007 food crisis. Rosegrant et al. (2008) simulated global biofuel production scenarios and pointed out the expansion of biofuel industry would result in major increase in global food prices. de Gorter and Just (2009) proposed a framework to study the effect of biofuel's consumer tax credit and contingent farm subsidy based on a price model that linked gasoline, ethanol, and corn. Balcombe and Rapsomanikis (2008) detected long-term relationships among the prices of oil, ethanol, and sugar prices in Brazil, the second largest biofuel production country in the world.

More investigations followed these foundational work. Overall, researchers tend to agree that biofuel was one of the causes of the recent global food price booms (Headey and Fan, 2008; Roberts and Wolfram, 2013; Rosegrant et al., 2008; Zilberman et al., 2013; de Gorter and Just, 2009; Tyner, 2010; Balcombe and Rapsomanikis, 2008) and biofuel policies across the world have created price links between energy and crops (Tyner, 2010; Serra et al., 2011; Serra, Zilberman, and Gil, 2011). In particular, Tyner (2010) believed that the price link between crude oil and corn could be severed by the E10 blend wall when oil price is high. However, researchers cannot agree on whether biofuel is the most important factor that induced the turmoil in the global food market and estimates of the amount of induced price increase differ significantly (Serra and Zilberman, 2013).

In general, researchers have used one of four approaches to gauge the impact of biofuel production on crop and energy prices: (1) the Marshallian supply and demand model, (2) the Marshallian supply and demand model with inventory, (3) time-series econometric analysis based on quarterly or annual data, and (4) time-series econometric analysis based on daily, weekly, and monthly data (de Gorter, Drabik, and Just, 2015). de Gorter, Drabik, and Just explained that approaches (1) and (3) tend to give little credit to biofuel policies for the rising crop prices while arguing a series of coincidental events had caused the food price crisis. Meanwhile, they also elaborated on how approach (2) usually models the new biofuel policies to cause kinks in the demand curve of crops, resulting in the argument of biofuel production to have major impact on crop prices. Last but not least, de Gorter, Drabik, and Just stated the empirical results using approach (4) are extremely variable despite often usage of the latest econometric techniques, stemming from researchers' misunderstanding of the relationship between some of the commodity price pairs.

We believe the combination of a more in-depth understanding of the US biofuel policies and some microeconomic theory fundamentals will contribute to the discussion of the crop and energy price linkages, and the results of the four approaches above may be improved with incorporation. Like US farm bills, US biofuel policies are complex, evolving, and influential as these tie the markets of energy and crop with ambitious policy goals. Moreover, the biofuel production industry in the U.S. is largely a policy-induced business that is still highly dependent on government's future decisions (taking the influential one dollar per gallon tax credit on biodiesel production as an example).

2.4 The Crop and Energy Price Links: A Model of Policies and Plant Operating Conditions

Building upon others' work and our understanding of the US biofuel policies, we discuss the variables, data, and price linkages of our crop and energy price linkage model.

As shown in Figure 2.4.1, we will use the following model.

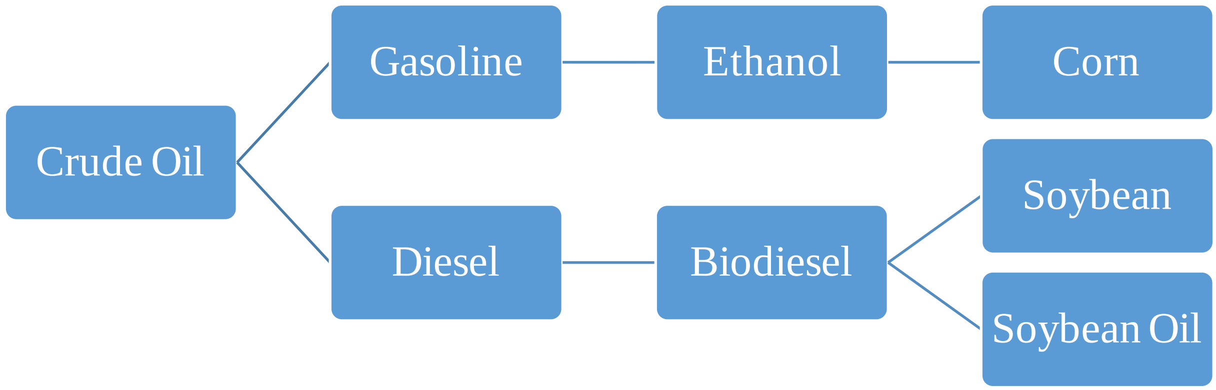

Figure 2.4.1 Crop and Energy Price Linkages in the Biofuel Era

The discussion of biofuels in this paper is limited to transportation fuels, including gasoline, diesel, ethanol, and biodiesel only. Though multiple feedstocks are available for the production of ethanol and biodiesel, we will focus on the most widely used corn (Department of Energy, 2017) and soybean oil (Wisner, 2013).

Figure 2.4.1 shows the main commodity prices used to study the energy and crop price links after the introduction of RFS. All prices, except biodiesel, are collected at the daily level beginning in January 2007. Weekly biodiesel prices are available starting April 2007. We focus our analysis on the monthly price data in Chapter 4. This choice helps us reduce short-term noise, such as the impact of minor accidents at refineries, while capturing the effects of major events like Hurricane Katrina and Rita.

Due to the long list of coefficients and variables used in this study besides those prices in Table 2.4.1, we provide detailed information for the rest of the data of the study in the data description component of the data files.

Table 2.4.1 Main Energy and Crop Commodity Price Data

Commodity	Description	Data Source
Crude Oil	Europe Brent Spot Price Free On Board (FOB), $/barrel	Energy Information Administration
Gasoline	New York Harbor Conventional Gasoline Regular Spot Price FOB, $/gallon	Energy Information Administration
Diesel	New York Harbor Ultra-Low Sulfur No 2 Diesel Spot Price, $/gallon	Energy Information Administration
Ethanol	Iowa Fuel Ethanol Price from a Representative Plant, $/gallon	CARD, Iowa State University
Biodiesel	Iowa Fuel Biodiesel Price from a Representative Plant, $/gallon	CARD, Iowa State University
Corn	Iowa Corn Price a Representative Plant Pays, $/bushel	CARD, Iowa State University
Soybean	Number 1 Yellow Soybeans, $/bushel	United States Department of Agriculture

To disentangle the relationship between crop and energy price linkages, we start with Figure 2.4.1. Unlike some other researchers, such as Nazlioglu and Soytas (2011), who directly study the price relationship between crude oil and crops, we break the energy and crop price linkages into three stages, namely the crude oil — energy (gasoline and diesel) link, the energy — biofuel link, and the biofuel — crop link. We believe this analysis framework can reveal how price transmission, linkage, and divergence occur for different reasons at each individual level, whereas lumping everything together through the crude oil and crop price linkage may not always pinpoint the specific causes of energy and crop price changes. The later scenario will impede policies' ability to address crop and energy price issues.

The crude oil — energy price linkage is the first layer of the analysis framework. In this paper, we are not concerned about the study of the supply and demand of crude oil that influences oil price levels. Rather, we are interested in the reasons in the divergence between crude oil and energy prices. The most common cause is unexpected shocks. When natural disasters hit, such as Hurricanes Katrina and Rita, refineries get destroyed or shut down. Even if there is no change in regional supply of crude oil, energy prices will rise in the short run due to production decrease with the loss in capacities. Seasonality may also be the reason. Gasoline tends to be sold at a premium when there is a lot of travel in the summer and diesel is in high demand during harvest season. Last but not least, input cost, such as the cost of natural gas and electricity, can also affect energy prices in the short run.

The energy — biofuel price link is policy-based and there are two different regimes under which the price link varies. As we mentioned earlier, the RFS has made the blending of certain amounts of ethanol and biodiesel into gasoline and diesel each year mandatory, making biofuels complements to gasoline and diesel. Under this scenario, consumers will have to use biofuel even if they would not otherwise, resulting in a price premium for biofuels, and we call that scenario the mandate premium regime (de Gorter, Drabik, and Just, 2015). Under this scenario, the price of biofuels can be higher than regular fuels. Alternatively, biofuel producers can also manufacture biofuels to compete against fuels as substitutes, and the federal government has offered both ethanol and biodiesel a blender's tax credit in the past to help the growth of the industry. In this situation, the energy content of biofuels (which is lower than regular fuels in terms of lower mileage per gallon) together with the tax credit will set a price floor for biofuels, and we call it a tax credit regime (de Gorter, Drabik, and Just, 2015). Under this scenario, the prices of biofuels are lower than regular fuels without tax credits. The price divergence between fuels and biofuels shall be guided by one of the two states. This price link, however, can be severed when production or marketing constraints of biofuels come into play.

Last but not least, the biofuel — crop price link can experience divergence when there are biofuel production capacity or marketing channel constraints as well. If biofuel production sites are running at full capacity and biofuels sell at a premium, crop prices will be higher than when the tax credit regime is binding. Marketing constraints will prevent more biofuels being blended, reducing the amount of crops used for biofuel production.

Besides the above new price linkages between crop and energy commodity pairs, crude oil still influences the prices of biofuels and crops through the input channel. As we have mentioned earlier, corn and soybean productions are both energy intensive. The production and blending of biofuels also require energy connected to crude oil. However, with the maturing of the US biofuel industry and the blend mandate being firmly in place, such influence is not as strong compared to the price links induced by biofuel productions.

In Chapter 2, we have built the theoretical analysis framework for crop and energy commodity prices that is dependent on biofuel polices. We will use the important concepts of the two states of nature in Chapter 3 for our empirical models.

CHAPTER 3

EMPIRICAL MODELS OF ENERGY AND CROP PRICE LINKS

Beginning in 2006, the fast growth in biofuel production under the new Renewable Fuel Standard (RFS) created a direct link between biofuels and food grains and oilseeds. Building upon others' findings and the relevant economic theories summarized from the literature in Chapter 2, this chapter will examine price links between corn and ethanol and soybean oil and biodiesel using time series empirical models. We will follow the flow diagram and channels presented in Figure 2.4.1 to study the links in the following order: crude oil and energy (gasoline and diesel), energy and biofuels (ethanol and biodiesel), and biofuels and crops (corn and soybean oil).

3.1 The Link between Crude Oil and Energy Prices

As we explained in Chapter 2, there are several possible reasons crude oil and energy (gasoline and diesel) prices can diverge. In fact, even gasoline and diesel prices do not hold a strict relationship, which we will show below. Hence, we are left with three price relationships to examine: crude oil –gasoline, crude oil-diesel, and gasoline-diesel. We can only estimate the first two of the three price relationships as the third falls out of an identity. Thus, we develop our empirical models to discuss these price links.

In general, the literature suggests three categories of factors that influence the link between crude oil and energy prices: the price of inputs, seasonality, and unexpected shocks. We examine each category in turn.

An oil refinery's operation requires the inputs of crude oil, natural gas, and electricity. During the refining process, crude oil is broken into oil products; some become final products and others are used to fuel the process together with natural gas and electricity. Depending on the contract delivery date of crude oil and the market price of oil products, oil refineries may use their crude oil stocks from the previous period and adjust their idle capacities during a certain production period to try to capture more revenue. Crude oil has been the largest input cost component of energy prices historically. According to EIA, crude oil consists of 51% and 47% of the retail prices of a gallon of gasoline and diesel consumers pay at gas stations in January 2017 (2017). The second biggest input cost rises from the refining of crude oil into petroleum products. Oil refining involves distillation, the process of separating crude oil into different products of various boiling points through heating, among many other steps. Major products of distillation include finished motor gasoline, distillate fuel oil (diesel and heating oil – otherwise identical products except color and tax), kerosene-type jet fuel, petroleum coke, still gas, liquefied refinery gas, residual fuel oil, and asphalt and road oil as shown in Table 3.1.0.1[1]. Besides main products like gasoline and diesel, oil refineries use some of the by-products, such as still gas, from the distillation process together with natural gas and electricity to power their operations[2]. In these ways, crude oil, natural gas, and electricity together make up the largest component of refining cost.

Seasonality in energy prices, including different consumption, production, and inventory patterns of petroleum products over a year, also affects price links. In general, consumers drive more over the summer and less in the winter, pushing refineries to stock up gasoline over winters and produce more gasoline in summers for the price premium. Meanwhile, the crop harvesting

[1] According to EIA, a 42-gallon barrel of crude oil yields about 19 gallons of gasoline, 12 gallons of ultra-low sulfur distillate (e.g. ULSD No. 2 Diesel), 4 gallons of jet fuel, 6 gallons of other products, 1 gallon of heavy fuel oil (residual), 2 gallons of hydrocarbon gas liquids, and 1 gallon of other distillates (heating oil) in 2015.

[2] Refineries can change their yields of petroleum products to adjust for seasonal demands within certain technology constraints albeit operation cost changes. This will have an impact on the by-products used to fuel their operations.

season every year induces a large amount of farm fuel consumption, causing a seasonal increase in diesel price. Heating oil is used for home heating in winters. Thus, oil refineries will adjust their productions to yield more distillate fuel oil to capture the diesel price premium while the gasoline price is seasonally lower. Moreover, refineries often conduct facility maintenance in the spring months, reducing overall refining capacities. When combining all these factors, these seasonal variations in demand and supply of petroleum products have a significant influence on price links.

Table 3.1.0.1 2015 US Refinery Yield Breakdown

Product	Percentage
Finished Motor Gasoline	46
Distillate Fuel Oil	29.5
Kerosene-Type Jet Fuel	9.6
Petroleum Coke	5.2
Still Gas	4.1
Liquefied Refinery Gas	3.7
Residual Fuel Oil	2.5
Asphalt and Road Oil	2
Other Products	3.8

Source: Refinery Yield, Petroleum & Other Products, EIA

Unexpected shocks, including natural, political, and accidental events, will also alter the links between crude oil and energy prices. Natural disasters disrupt oil production in different ways, such as the destruction of production facilities and the increasing of shut-in wells (non-operating wells capable of production). Hurricane Katrina and Rita each landed in the Gulf of Mexico (GOM) in August and September of 2005. The two hurricanes destroyed 113 platforms (Oynes, 2006) and the total capacity of shut-in wells was equivalent to 97.83% of GOM's daily oil production at the end of September 2005 (MMS, 2005). Political events also influence the flow of crude oil and energy in the international market. To retaliate against the United States' support of Israel during the 1973 Arab-Israel War, OPEC members imposed an embargo that both banned petroleum exports to the U.S. and cut their oil production. With U.S. energy prices quadrupling and the weakening of the U.S. dollar, OPEC members succeeded in forcing the Nixon Administration to enter peace negotiations as it attempted to avert an eminent recession in an economy overly reliant on foreign oil supply (Department of State, 2017). Last but not least, accidents, such as refinery explosion, cause distortions to (regional) energy price relationships. Two major refinery explosions occurred in California in 2015 and 2016. In 2016, Buhl estimated the 2015 ExxonMobil explosion in Torrance would make Californian motorists pay at least $2.4 billion more for energy in the six months that followed. Thus, though less frequent, these natural, political, and accidental events can sever the price links between crude oil and energy despite the effort through domestic reserve, regional redistribution, and foreign import to contain them.

Besides of these three categories of factors, we also include some common tools in time-series data analysis: trend and autoregressive (AR) variables. When a time-series variable displays a trend, its observations show a certain pattern with or without smoothing or function-fitting (such as logarithmic, exponential, and polynomial specifications). Any country's annual nominal GDP across years, for example, often displays an upward trend in the absence of recession. On the other hand, past values often have an impact on the present value of a time-series variable, making their inclusion in the analysis essential. As OPEC members continued the oil embargo against the U.S. in 1973, gasoline price double, tripled, and quadrupled in several months with the U.S. failing to acquire additional oil supply from its European and Asian allies (Department of State, 2017).

We use Model 3.1.0.1 below to study crude oil energy price links, where i = G or D (gasoline or diesel). P_{CO_t}, P_{NG_t}, and P_{E_t} each represents crude oil, natural gas, and electricity price in a certain period. Using the augmented Dickey-Fuller test (unit root test), we found the prices of crude oil, gasoline, diesel, natural gas, electricity are all non-stationary while the aggregate idle capacities of oil refineries and refineries' crude oil stock to be stationary. However, the five non-stationary prices are all integrated of order one (their first differences are stationary) and the error resulted from using the non-stationary regression variables is stationary. Hence, the prices of gasoline (P_{g_t}) and diesel (P_{d_t}) are co-integrated with the prices of crude oil, natural gas, and electricity with similar stochastic trends. The results of least square estimation therefore won't be spurious and we are safe to proceed. This result is not surprising based on our discussion of the relationships among these commodities above.

$$P_{Gasoline\ or\ Diesel_t} = f(intercept, P_{Crude\ Oil_t}, P_{Natual\ Gas_t}, P_{Electricity_t}, P_{Crude\ Oil_{t-1}}, P_{Natual\ Gas_{t-1}}, P_{Electricity_{t-1}}, P_{Gasoline_{t-1}}\ or\ P_{Diesel_{t-1}}, refineries'\ idle\ capacity, refineries'\ crude\ oil\ stock, monthly\ dummies, unexpected\ shock\ dummies, trends, error) \quad (3.1.0.1)$$

*t refers to a variable's value in month t. t-1 refers to the variable's value in the previous month.

3.1.1 The Link between Crude Oil and Gasoline Prices

The first model links crude oil (P_{CO}) and gasoline prices (P_G). For production inputs, we include the prices of crude oil, natural gas, and electricity and plus a measure of idle refinery capacity and refineries' crude oil inventories. For seasonality, we use monthly dummies given we are using monthly price data. For unexpected shocks, we define any observation that is three standard deviations away from the mean as an outlier (Barnett and Lewis, 1984) and give it a dummy. Last but not least, we use trends and AR(1) terms for all the input and gasoline prices.

Before applying the ordinary least square (OLS) analysis, we first identified outliers in the monthly gasoline prices (g). Table 3.1.1.1 shows all observations were within three standard deviations of the mean and no outliers were identified for unexpected shocks.

Table 3.1.1.1 Outlier Test of Gasoline Price

Variable	Obs	Mean	Std. Dev.	Min	Max
g	366	51.76477	35.52321	12.894	138.264

We then ran an OLS regression with all the variables, predicted monthly gasoline prices, and identified zero outlier in prediction errors (gd) with Table 3.1.1.2.

Table 3.1.1.2 Outlier Test of Prediction Error of Gasoline Price

Variable	Obs	Mean	Std. Dev.	Min	Max
gd	189	-9.35e-08	3.178768	-7.801574	9.407989

Table 3.1.1.3 shows the regression results. We first focus on explaining the factors that do not affect gasoline price. As shown in Figure 3.1.1.1, refineries' crude oil stock has little influence on the price of gasoline with its small weight in the total crude oil stock of the United States with and without Strategic Petroleum Reserve. Oil refineries often sign contracts for product delivery and buy delivery contracts of crude oil at certain dates and prices to hedge price risk. Due to the market's competitive nature, refineries' excessive oil stock is often limited compared to their monthly production level as shown in Figure 3.1.1.2. Thus, crude oil stocks is not an important explanatory variable. The prices of electricity and natural gas both have a negligible influence on gasoline prices mainly due to their limited use. By-products of oil refining supply most of the energy and refineries only use an amount of "natural gas and electricity with energy equivalent to 3% of the crude oil processed (Knittel and Smith, 2015)."

Meanwhile, the price of crude oil, oil refineries' idle capacities, monthly dummies, and a lagged dependent variable (the price of gasoline in the previous month) are significant variables that affect gasoline prices. As the major input, the price of crude oil directly impacts gasoline's price. If an unexpected event, such as Hurricane Katrina, hits a region and decreases local refinery capacities, refineries elsewhere will be forced to supply the national market with more

Table 3.1.1.3 OLS Regression of Gasoline Price on Crude Oil Price

	Gasoline Price
crude oil	0.983***
	(20.35)
refineries' crude oil stock	0.0000479
	(0.51)
refineries' idle capacity	0.00380***
	(3.76)
natural gas	0.344
	(0.76)
electricity	-0.605
	(-0.19)
linear trend	0.141
	(1.34)
quadratic trend	-0.000170
	(-0.96)
January	0.803
	(0.59)
February	0.928
	(0.69)
March	2.662
	(1.81)
April	4.960**
	(3.26)
May	3.946*
	(2.42)
June	2.966
	(1.43)
July	3.596
	(1.86)
August	4.271*
	(2.40)
September	3.305
	(1.97)
October	0.842
	(0.52)
November	0.452
	(0.31)
crude oil previous month	-0.585***
	(-6.94)
gasoline previous month	0.569***
	(8.49)
refineries' crude oil stock	-0.0000933
previous month	(-0.99)
refineries' idle capacity previous	-0.00283**
month	(-2.70)
natural gas previous month	-0.0608
	(-0.14)
electricity previous month	-1.366
	(-0.45)
constant	-6.397
	(-0.36)
Observations	189
R-squared	0.9904
Adjusted R-squared	0.9890

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

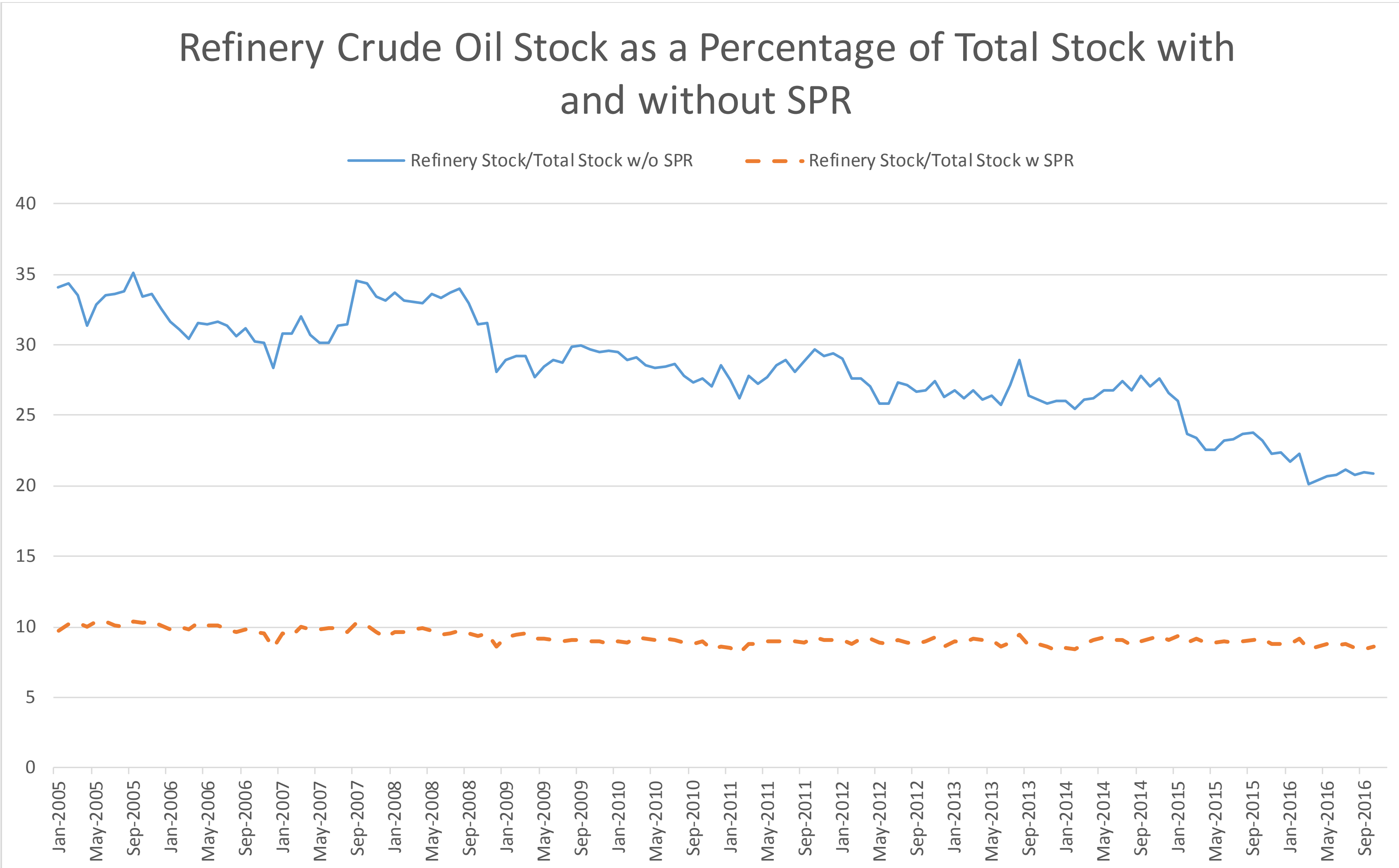

Figure 3.1.1.1 Refinery Stock as a Percentage of Total Stock with and without SPR

Source: U.S. Total Stocks (Thousand Barrels), Monthly, EIA

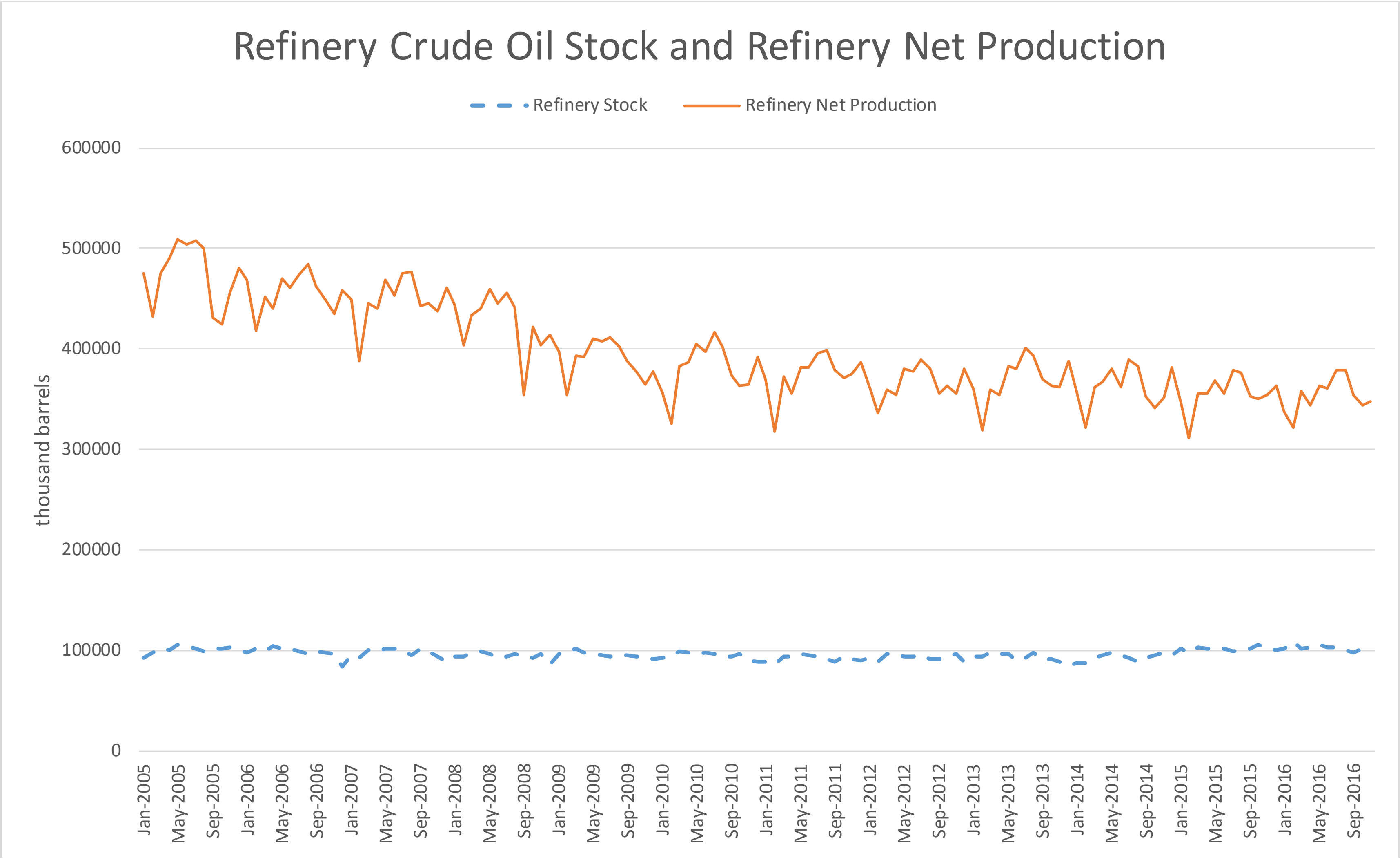

Figure 3.1.1.2 Refinery Crude Oil Stock and Net Production

Source: Refinery Net Production (Thousand Barrels), Monthly, EIA oil products *ceteris paribus*. The amount of excess capacity these unaffected plants owns will determine the extent of gasoline price increase. Monthly dummies overall match our previous prediction. Using December as the basis of comparison, gasoline prices in November, January, February, and March (the winter season) are not different from December's value. Price picks up in April, continues to rise in May, and stays more or less the same except for an increase in August before it reaches a low in October. With the short interim period, gasoline prices in the last month will influence the value of the current month.

We have not detected any shock that has disrupted the price link between crude oil and gasoline in the period of study. While Hurricane Katrina and Rita caused serious damage after they landed in the southern part of the U.S., gasoline price in New England seems to remain largely unaffected. Political events appears not to cause major disruption to the crude oil market in the U.S. during the last decade. Besides refinery accidents, U.S. production level of crude oil took off near the end of 2010s, contributing towards greater level of energy security and independence (EIA, 2017).

Overall, crude oil prices, seasonality, past prices, and supply and demand conditions are the significant variables that affect the link between gasoline and crude oil prices in the past ten years.

3.1.2 The Link between Crude Oil and Diesel Prices

The second model links crude oil (P_{CO}) and diesel prices (P_D). Similar to gasoline's case, the same factors of production are assessed: inputs, seasonality, and unexpected shocks influence diesel prices. We also include trends and AR(1) terms to improve the model's explanation power.

In Table 3.1.2.1, we first perform an outlier check of diesel prices (d) and no significant outliers are found.

Table 3.1.2.1 Outlier Test of Diesel Price

Variable	Obs	Mean	Std. Dev.	Min	Max
d	126	99.95267	29.29784	41.118	163.254

We then ran an OLS regression with all the variables in predicting monthly diesel prices. One outlier was identified in the prediction errors (dd). After giving the outlier a dummy, we ran the OLS regression again.

Table 3.1.2.2 Outlier Test of Prediction Error of Diesel Price

Variable	Obs	Mean	Std. Dev.	Min	Max
dd	124	-1.07e-07	2.424837	-5.996594	9.811692

Table 3.1.2.3 shows the results of the two regressions. After removing the outlier of the price shock (March 2008), the outcome is similar to that of the crude oil and gasoline price link. Crude oil prices, idle capacity, and a lagged dependent variable are significant variables affecting diesel prices. Refineries' crude oil inventories and the prices of natural gas and electricity are not found to have significant impacts on the diesel price. Though the coefficient of the electricity price in the previous month is negative, technology advancement is unlikely to happen so fast such that refineries can use less electricity and reduce costs. As predicted, diesel sells at a premium during the harvesting season each year in October and the price increases again when winter begins in November.

Table 3.1.2.3 OLS Regression of Diesel Price on Crude Oil Price

	(1) Diesel Price	(2) Diesel Price
crude oil	0.968***	0.966***
	(21.21)	(23.01)
refineries' crude oil stock	0.0000280	0.000000946
	(0.26)	(0.01)
refineries' idle capacity	0.00178	0.00198*
	(1.87)	(2.25)
natural gas	1.188*	0.843
	(2.14)	(1.63)
electricity	5.726	5.145
	(1.71)	(1.67)
linear trend	-0.109	-0.236
	(-0.26)	(-0.62)
quadratic trend	0.000219	0.000418
	(0.34)	(0.70)
January	2.122	2.250
	(1.42)	(1.63)
February	2.415	2.576
	(1.71)	(1.98)
March	2.233	1.110
	(1.35)	(0.72)
April	2.473	2.517
	(1.52)	(1.68)
May	1.193	1.421
	(0.69)	(0.89)
June	-0.350	0.0203
	(-0.14)	(0.01)
July	0.800	0.766
	(0.30)	(0.31)
August	4.278	3.812
	(1.57)	(1.52)
September	4.092	3.386
	(1.64)	(1.47)
October	5.683**	5.124*
	(2.68)	(2.62)
November	4.371**	4.128**
	(2.76)	(2.83)
crude oil previous month	-0.691***	-0.714***
	(-7.93)	(-8.88)
diesel previous month	0.750***	0.772***
	(11.13)	(12.41)
refineries' crude oil stock	-0.00000752	-0.0000175
previous month	(-0.07)	(-0.18)
idle capacity previous month	-0.000513	-0.000359
	(-0.53)	(-0.40)
natural gas previous month	-0.669	-0.553
	(-1.17)	(-1.05)
electricity previous month	-7.393*	-6.099*
	(-2.25)	(-2.01)
outliers of predicted diesel price		11.89***
		(4.34)
Constant	18.00	37.83
	(0.34)	(0.78)
Observations	124	124
R-squared	0.9932	0.9943
Adjusted R-squared	0.9915	0.9928

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.1.3 Linking Crude Oil, Gasoline, and Diesel Prices through the Crack Spread

Analysts often use the term "crack spread" to obtain a rough estimate of refineries' profits. The term refers to the price differential between processed oil products (outputs of gasoline and diesel) and crude oil (input). Some commonly used ratios include 3:2:1, 5:3:2, and 2:1:1. For example, a 3:2:1 spread means every three barrels of crude oil would yield two barrels of gasoline and one barrel of diesel. By taking the price difference between the sum of gasoline and diesel and crude oil, analysts will have some idea about the refineries' profits.

In reality, the calculated crack spread also contains the component of processing costs of refineries on top of profits. Equation 3.1.3.1 shows the relationship among the three products, where P_{CS_t} is the crack spread per barrel, P_{G_t} is the gasoline price per barrel, P_{D_t} is the diesel price per barrel, and P_{CO_t} is the crude oil price per barrel in time period t.

$$P_{CS_t} = \frac{2}{3} P_{G_t} + \frac{1}{3} P_{D_t} - P_{CO_t} \qquad (3.1.3.1)$$

The main purpose for examining the crack spread is to see whether the implementation of the blend mandate has brought any change to the trend of the crack spread. Figure 3.1.3.1 shows the history of the crack spread. Due to data availability, however, we have no information of the spread before the implementation of the blend mandate. Since 2006, the crack spread has been rather unstable, being the lowest between 2009 and 2011 while fluctuating significantly between 2006 and 2008 and in 2013.

As the crack spread is a derived value, prices and quantities (such as inventories and idle capacities) of oil and oil products cannot serve as independent variables in the regression model (3.1.3.2) due to the multicollinearity issue. Thus, besides the variables of seasonality and unexpected shocks, we use a trend and AR(1) terms in the model of Equation 3.1.3.2.

$$P_{CS_t} = f(intercept, seasonality, unexpected\ shocks, linear\ trend, P_{CS_{t-1}}, and\ error)$$

(3.1.3.2)

We first examine if there is any outlier in P_{CS_t} (cs) and no outlier is found as shown in Table 3.1.3.1 below.

Table 3.1.3.1 Outlier Test of the Crack Spread

Variable	Obs	Mean	Std. Dev.	Min	Max
cs	126	12.6701	3.870704	6.172	24.266

We ran an OLS regression with all the variables to predict monthly crack spreads, and identified two outliers in the prediction errors (csd) in Table 3.1.3.2. After giving each a dummy, we ran the OLS regression again and Table 3.1.3.3 shows the results of the two regressions.

Table 3.1.3.2 Outlier Test of the Crack Spread Prediction Error

Variable	Obs	Mean	Std. Dev.	Min	Max
csd	125	3.07e-09	2.624792	-6.330684	10.69226

Ignoring the outliers, seasonality has a stronger impact on crack spread than the lagged term. Using December as the basis of comparison, crack spreads are higher in late spring and early summer. Factors such as plant maintenance in the spring and higher gasoline price in the summer during the travel season may have contributed to this seasonal premium.

Other than that, the limited explanation power of the model and the variations in the crack spread do not provide much more additional information on how gasoline and diesel prices interact with each other.

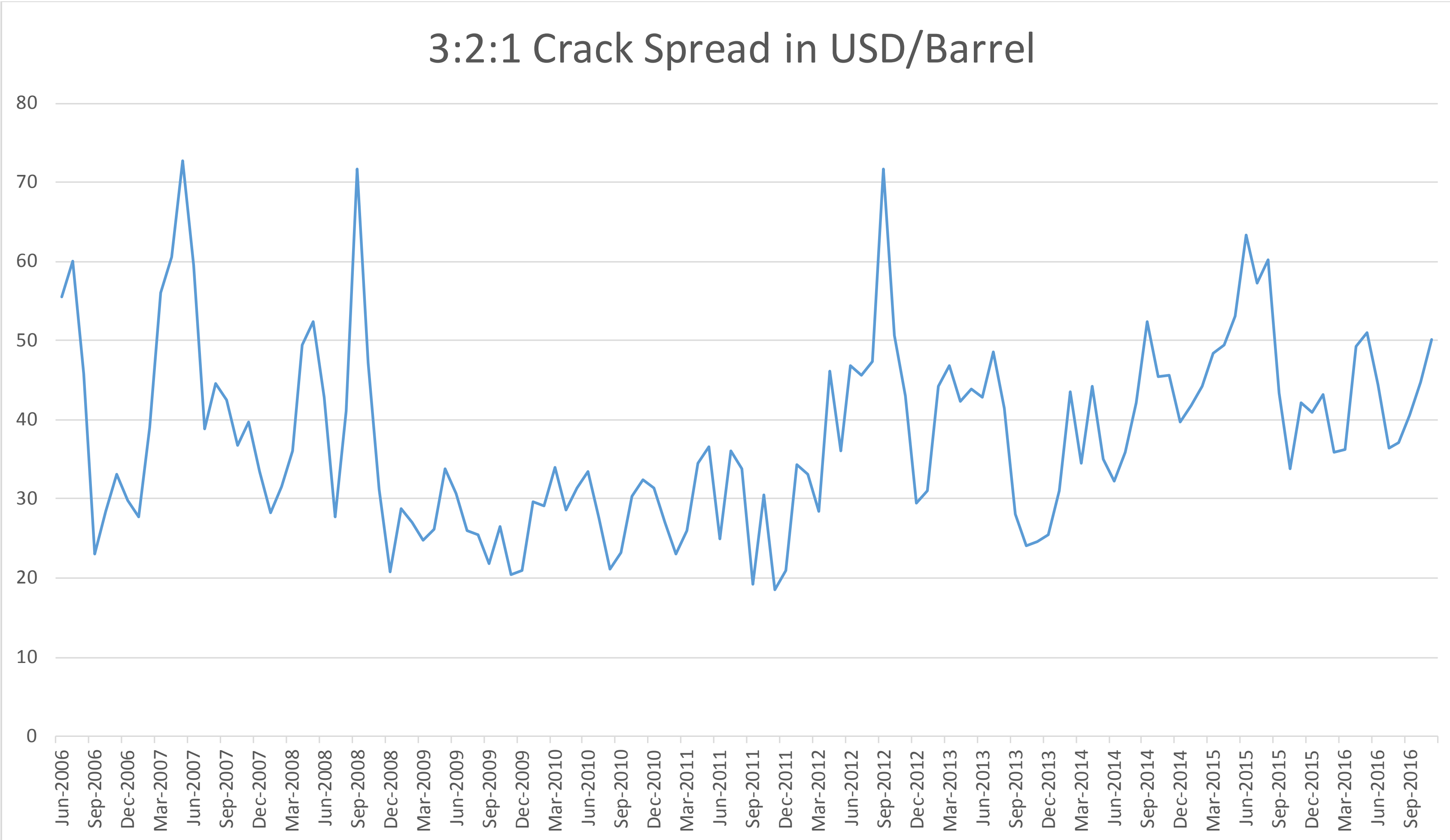

Figure 3.1.3.1 3:2:1 Crack Spread

Source: Europe Brent Spot Price FOB, New York Harbor Conventional Gasoline Regular Spot Price FOB/Ultra-Low Sulfur No 2 Diesel Spot Price, Monthly, EIA

Table 3.1.3.3 OLS Regression of the Crack Spread

	(1) Crack Spread	(2) Crack Spread
linear trend	0.00877	0.0109
	(1.26)	(1.83)
January	1.817	1.784
	(1.46)	(1.68)
February	2.088	2.076
	(1.68)	(1.96)
March	2.145	2.154*
	(1.73)	(2.03)
April	3.669**	3.694***
	(2.95)	(3.48)
May	2.865*	2.936**
	(2.27)	(2.72)
June	1.676	1.758
	(1.32)	(1.62)
July	1.305	1.387
	(1.06)	(1.31)
August	2.031	2.083*
	(1.66)	(1.99)
September	1.952	-0.191
	(1.60)	(-0.17)
October	0.802	0.848
	(0.66)	(0.81)
November	1.043	1.058
	(0.86)	(1.02)
crack spread last month	0.661***	0.636***
	(9.33)	(10.49)
outlier of predicted		12.06***
crack spread		(6.49)
constant	-0.164	-0.538
	(-0.07)	(-0.27)
Observations	125	125
Adjusted R-squared	0.4808	0.6213

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.2 The Link between Energy and Biofuel Prices

Depending on which biofuel policy regime (tax credit or mandate premium) explained in Chapter 2 is binding, biofuels can either be complements or substitutes for oil products. When the mandate is binding, biofuels are complements with their energy product counterparts. The ban of MTBE in the early 2000s and the enforcement of the 2005 and 2007 RFS blending mandate have stimulated a sharp increase in the production of both ethanol and biodiesel. The majority of gasoline sold at pumps today uses ethanol as an oxygenate and carries roughly 10 percent of fuel ethanol (hitting the blend wall where regular cars cannot consume fuel with more than 10 percent ethanol). Similarly, retail diesel is often a mixture of regular diesel and biodiesel based on different blend specifications. Meanwhile, when the tax credit is binding (no mandate premiums), ethanol and biodiesel are substitutes for energy and both prices hit the minimum price floor. Moreover, ethanol is also a close substitute to conventional gasoline when used in flex-fuel vehicles. We use the above two policy regimes for empirical analysis of the energy and biofuel price links.

3.2.1 The Link between Ethanol and Gasoline Prices

Since 2006, the interaction between the prices of gasoline (P_G) and ethanol (P_E) has become dependent on the two regimes discussed above (henceforth referred to as "two states of nature"). Each year, consumers demand a certain amount of ethanol for purposes like oxygenate or fuel in the absence of a blend mandate and tax credits. However, as the Environmental Protection Agency (EPA) started to require the blending of ethanol into retail gasoline with the RFS in 2005, consumers now must consume a certain amount of ethanol with their purchase of retail gasoline every year even if they would not have done so otherwise. The yearly target amount of ethanol changes over time as EPA converts a volumetric (a fixed volume target each year) and with a fractional (a fixed percentage target) mandates. Moreover, to encourage the production of ethanol, government has provided a tax credit for producers in the first few years. These policy interventions have led to the existence of two states of nature.

The relationship between the prices of gasoline and ethanol depends on which regime is binding. A blend mandate requires consumers to use more ethanol than they would otherwise and consumers will have to pay for a higher P_E as shown in Chapter 2. When consumers demand more ethanol than EPA's annual requirement, we say the tax credit regime is binding and P_G and P_E are locked onto each other as fuel substitutes. The equation below describes the pair's relationship under the two regimes. The variable representing the ethanol price P_E is supposed to be the lowest under the tax credit regime.

The price relationship under a blend mandate regime is given by Equation 3.2.1.1, where P_F refers to fuel (the mixture of ethanol and gasoline) price and α represents the fraction of ethanol required in the total fuel mix.

$$P_F = \alpha P_E + (1 - \alpha) P_G \qquad (3.2.1.1)$$

The price relationship under a tax credit regime is given by Equation 3.2.1.2, where $\lambda =$ 0.70 refers to the amount of miles a gallon of ethanol achieves compared to a gallon of regular gasoline (de Gorter, Drabik, and Just, 2015). The volumetric fuel tax is represented by t and t_t is government's tax credit for fuel blenders.

$$P_E^* = \lambda P_G - (1 - \lambda) t + t_t \qquad (3.2.1.2)$$

Keeping in mind the implication of the two different regimes, we now examine the relationship between ethanol and gasoline prices. For a given gasoline price, we first predict the ethanol price P_E^* using Equation 3.2.1.2 and then take the difference between P_E and P_E^* to derive the term we call the mandate price premium. In theory, when the mandate price premium is high, the blend mandate regime should be binding and consumers will have to pay for a higher ethanol price. As the ethanol price under such circumstance does not reflect its real value as a fuel, P_G and P_E become delinked. Alternatively, if the mandate premium is low, P_G and P_E should be closely linked under the tax credit regime.

Table 3.2.1.1 shows the result of our test of the above hypothesis with the correlation between P_G and P_E. In theory, the correlation is expected to be low, if not negative, when the mandate premium is high, but positive and high when the tax credit is binding. Mandate premium are the lowest when we only include the observations below the first quartile (bottom 25% of the values), and the correlation we get is 0.8613. Similarly, mandate premium is the highest when we only include the observations above the third quartile (top 25% of the values), and the correlation we get is 0.9099. This does not match with our prediction. Moreover, as we continue to drop observations of smaller values of mandate premium across quartiles to obtain correlations, the values increase instead of decrease.

Table 3.2.1.1 Correlations between Gasoline and Ethanol Prices

Mandate Premium	No. of Observations	Correlation
Full Sample	123	0.8162
Observations below the First Quartile	31	0.8613
Observations above the First Quartile	92	0.8439
Observations above the Median	62	0.8617
Observations above the Second Quartile	61	0.8593
Observations above the Third Quartile	30	0.9099

To study this same link, we also examine the relationship between the percentage changes in P_G and P_E ($\%\Delta P_G$ and $\%\Delta P_E$) from the previous month by taking their differences. In theory, under the tax credit regime, $\%\Delta P_G$ and $\%\Delta P_E$ should move in the same direction (either increase or decrease) if no shocks affect the crude oil and gasoline price link and the difference between their magnitudes should be small in a certain period. Alternatively, under the blend mandate regime, $\%\Delta P_G$ and $\%\Delta P_E$ should go in opposite directions (unless exogenous shocks induce a drop in supply in gasoline, forcing P_G to go up) with the relationship in Equation 3.2.1.1 and the difference between their magnitudes should be large most of the time in a certain period.

Following this reasoning, we divide the data into three groups and check their correlations individually. The first group of data reflects the situation when the tax credit regime is binding. After keeping the observations whose $\%\Delta P_G$ and $\%\Delta P_E$ move in the same direction (either increasing or decreasing), we use the sample mean of the absolute values of the difference between $\%\Delta$ in P_G and P_E as a reference. If the absolute value is smaller than the sample mean, we keep it. Otherwise, we drop it. The second group of data captures the condition when the blend mandate regime is binding. After keeping the observations whose $\%\Delta P_G$ and $\%\Delta P_E$ move in the opposite directions, we use the sample mean of the absolute values of the difference between $\%\Delta$ in P_G and P_E as a reference. If the absolute value is bigger than the sample mean, we keep it. Otherwise, we drop it. The third group of data consists observations that do not belong to the first two groups.

We have mixed results from Table 3.2.1.2. At one hand, when the prices of ethanol and gasoline move together under the tax credit regime, the removal of observations above sample mean should yield higher correlation values but does not. Meanwhile, in those months when gasoline and ethanol prices move in different directions, the correlation between the two variables falls, as predicted, when we select the sample above the mean value.

Table 3.2.1.2 Correlations between Percentage Change in Ethanol and Gasoline Prices

$\lvert \%\Delta P_E - \%\Delta P_G \rvert$	Group	No. of Observations	Correlation
Full Sample	1	72	0.8184
Sample of Observations below Sample Mean	1	47	0.8005
Full Sample	2	52	0.8190
Sample of Observations above Sample Mean	2	20	0.7307

As shown in Figure 3.2.1.1, ethanol and gasoline prices do not always track each other. Notably, the prices moved in different directions in late 2006 to early 2007, mid-2009, 2010, and late 2011 through the first quarter of 2014. Meanwhile, Figure 3.2.1.2 shows us the predicted ethanol price under the tax credit binding regime also tracks the overall price trend poorly in some of these periods while it generally follows the actual price in other periods. During the periods of ethanol and gasoline prices tend to diverge, actual ethanol price did not always lie above the theoretical price floor, such as in mid-2009 and early 2010, but otherwise corresponded to positive mandate premiums most of the time. This result seems to confirm our model's validity as we incorporate other factors, such as ethanol production capacity over years, to account for unexplained anomalies.

Figure 3.2.1.3 shows how U.S. ethanol production has leveled off since 2006. For the period from 2011 onward, predicted ethanol prices have been consistently lower than the actual ethanol prices. Meanwhile, as ethanol production capacity continued to increase between 2006 and 2010, there were periods in which the actual market prices were lower than the predicted prices. Such occurrences in the early years signaled an over-supply of ethanol in the market and one possible reason was that retailers and consumers were not able to handle the fast increase in ethanol consumption requirement due to the existence of the blend wall. For retailers, oil companies may not be able to help them upgrade the pumps, transport tools, and storage

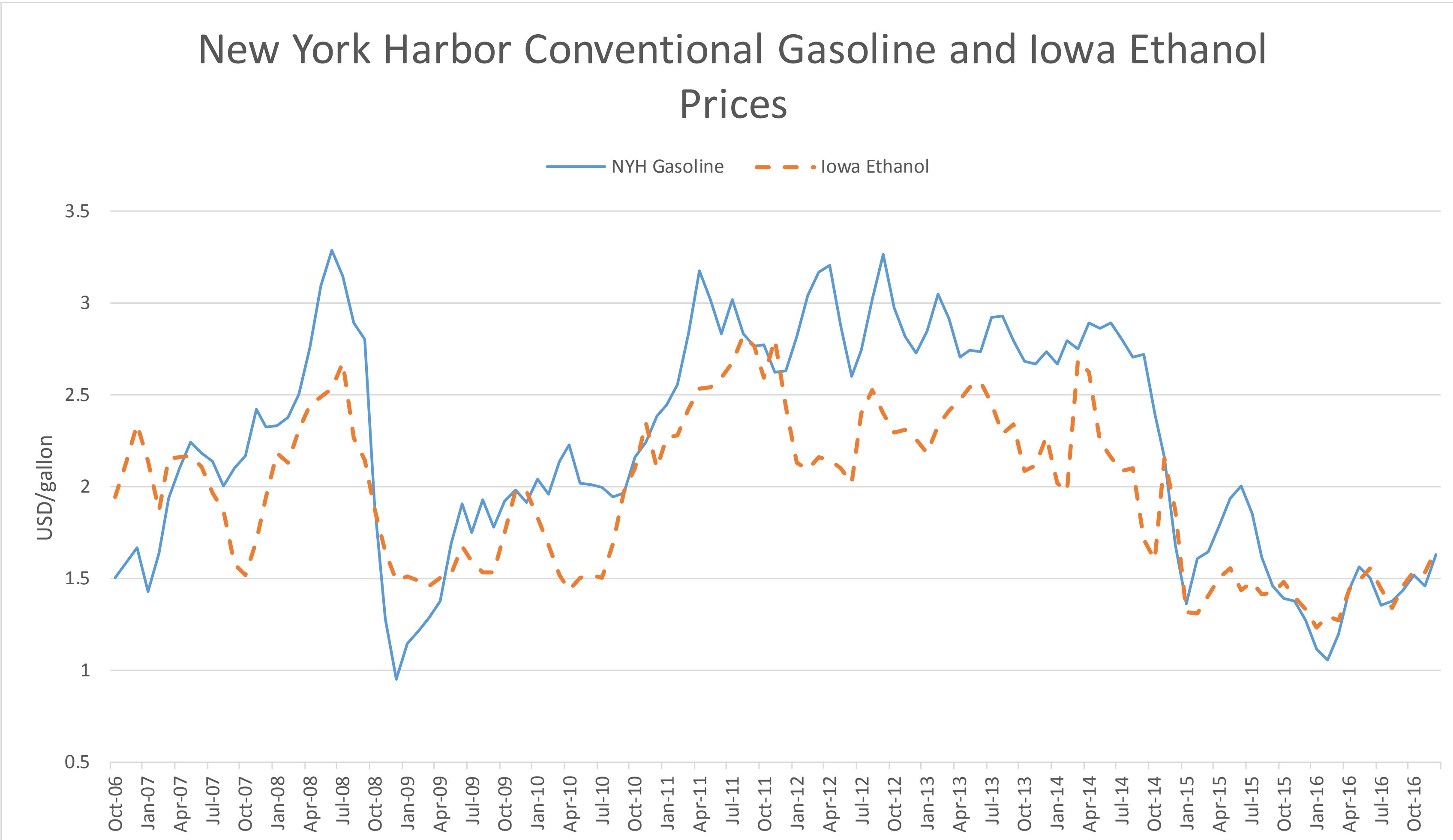

Figure 3.2.1.1 New York Harbor Gasoline and Iowa Ethanol Prices

Source: New York Harbor Conventional Gasoline Regular Spot Price FOB (Dollars per Gallon), Monthly, EIA

Ethanol Price, Historical Ethanol Operating Margins, CARD, ISU

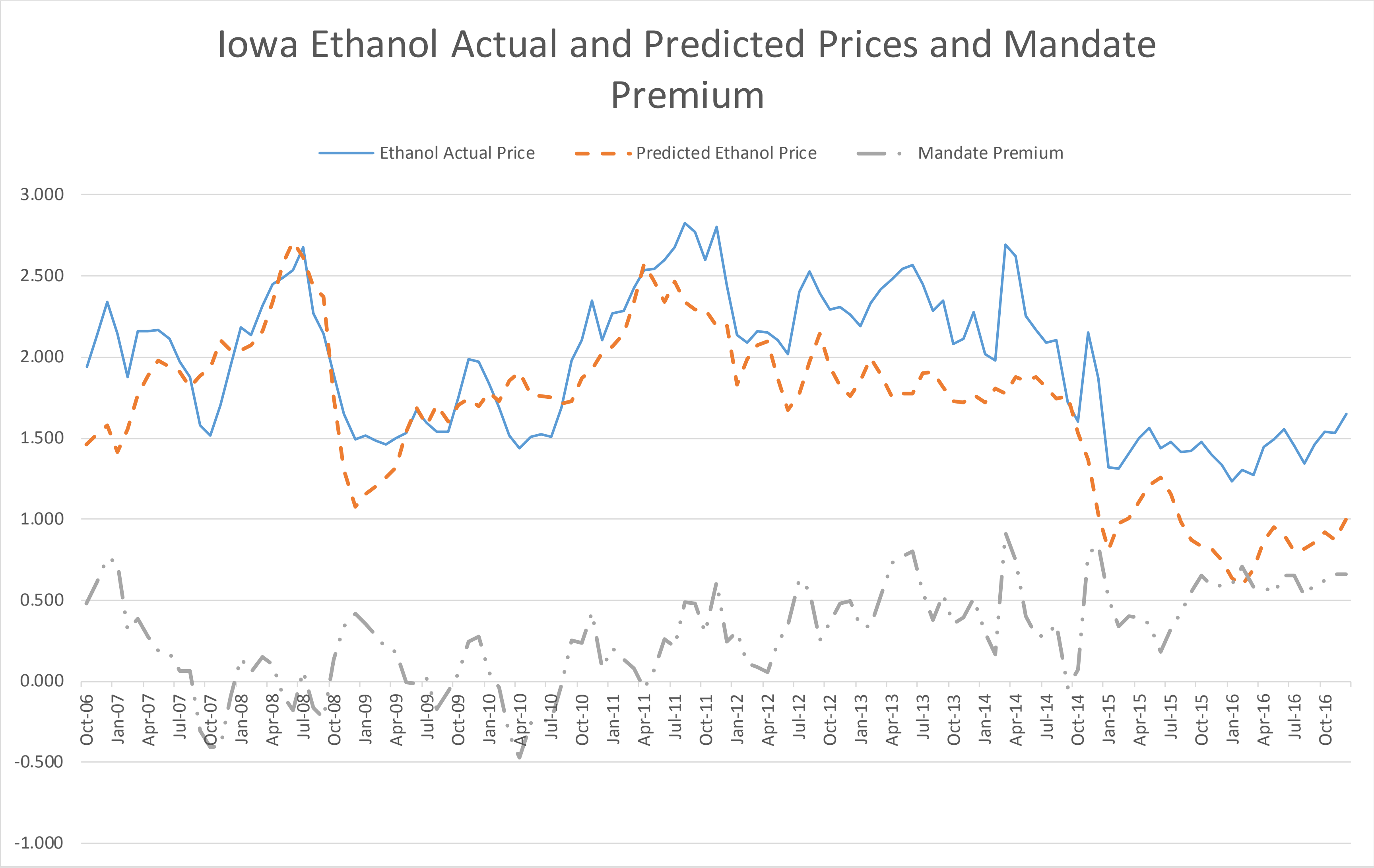

Figure 3.2.1.2 Iowa Actual and Predicted Ethanol Price and Mandate Premium

Source: Ethanol Price, Historical Ethanol Operating Margins, CARD, ISU

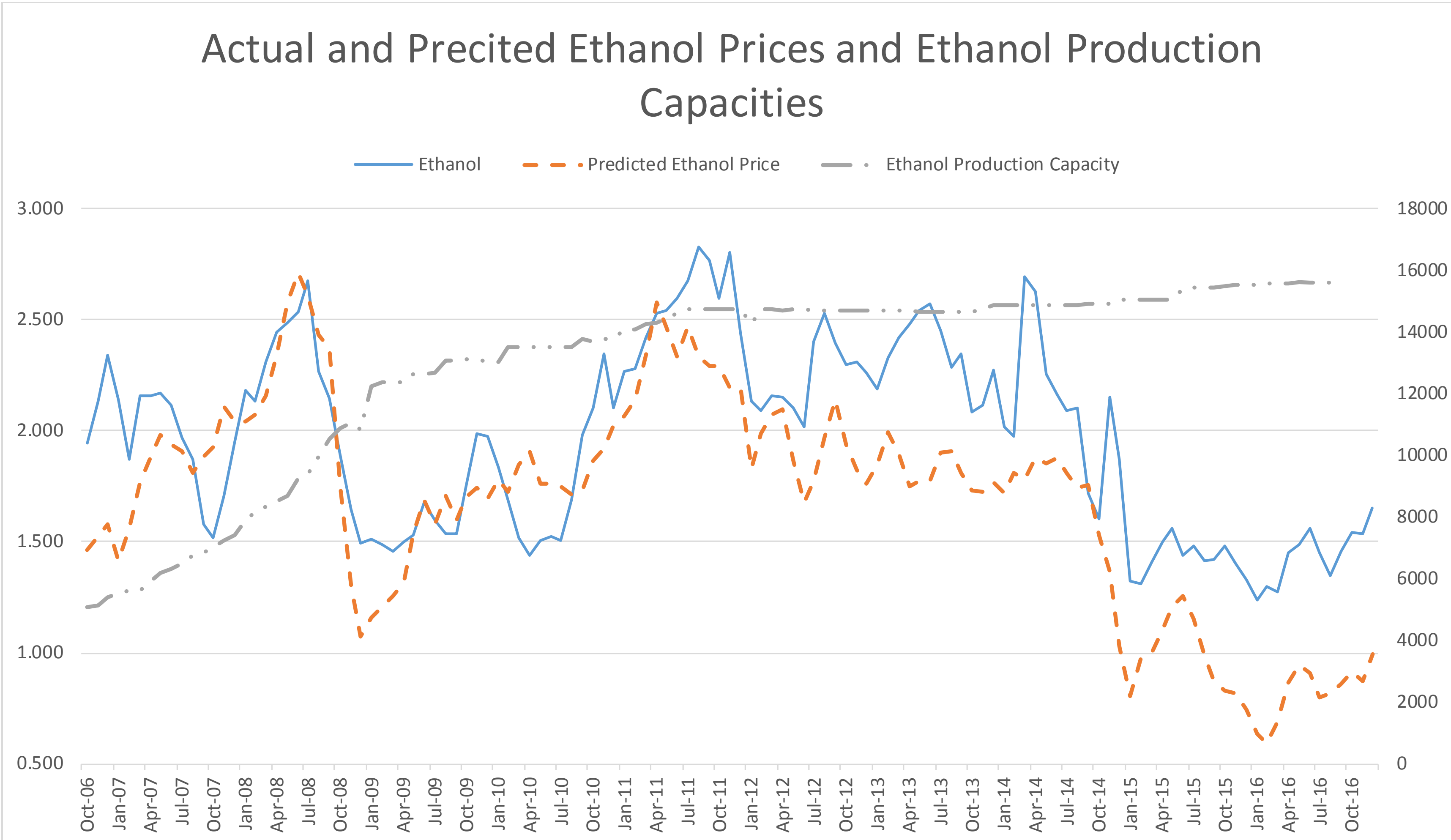

Figure 3.2.1.3 Iowa Actual and Predicted Ethanol Price and U.S. Ethanol Production Capacity

Source: Ethanol Price, Historical Ethanol Operating Margins, CARD, ISU

Ethanol Production Capacity by Plant, Nebraska Government facilities for the mixed fuel fast enough; and for consumers, their car engines may not be able to handle a fuel with more than 10 percent ethanol without incurring any damage. Other reasons for the actual price being lower than the predicted price may include import of foreign ethanol in the short term to meet an annual blend goal.

We use Model 3.2.1.1 to study the mandate premium. The tax credit dummy is 1 if the government offers a blender's tax credit. For the mandate premium dummy, it is 1 if the mandate premium falls below 0.

$$MP_t = f(intercept, linear\ trend, quadratic\ trend, monthly\ dummies, tax\ credit\ dummy, mandate\ premium\ dummy, MP_{t-1}, outlier\ dummy, error) \quad (3.2.1.1)$$

We examine if there is any outlier in the mandate premium and Table 3.2.1.3 reports there is no outlier.

Table 3.2.1.3 Outlier Test of the Mandate Premium

Variable	Obs	Mean	Std. Dev.	Min	Max
mp_NY	123	0.2880204	0.2992867	-0.4705	0.9155905

We then run an OLS regression with all the variables to predict the mandate premium, and identified one outlier in the prediction errors (mpdd) in Table 3.2.1.4. After giving it a dummy, we ran the OLS regression again and Table 3.2.1.5 shows the results of the two regressions.

Table 3.2.1.4 Outlier Test of the Mandate Premium Prediction Error

Variable	Obs	Mean	Std. Dev.	Min	Max
mpdd	122	-1.29e-09	0.1381056	-0.3239646	0.5737674

Table 3.2.1.5 OLS Regression of the Ethanol Mandate Premium

	(1) Mandate Premium	(2) Mandate Premium
linear trend	-0.000972	-0.00107
	(-0.57)	(-0.68)
quadratic trend	0.0000160	0.0000165
	(1.26)	(1.41)
January	-0.0896	-0.0877
	(-1.37)	(-1.46)
February	-0.147^{*}	-0.144^{*}
	(-2.26)	(-2.41)
March	-0.0356	-0.0945
	(-0.54)	(-1.52)
April	-0.0824	-0.0787
	(-1.26)	(-1.31)
May	-0.0691	-0.0647
	(-1.05)	(-1.07)
June	-0.0477	-0.0423
	(-0.72)	(-0.69)
July	-0.0791	-0.0723
	(-1.19)	(-1.18)
August	-0.0475	-0.0429
	(-0.72)	(-0.71)
September	-0.0575	-0.0534
	(-0.87)	(-0.87)
October	-0.0889	-0.0813
	(-1.33)	(-1.32)
November	0.0791	0.0841
	(1.23)	(1.42)
tax credit dummy	-0.0452	-0.0293
	(-0.80)	(-0.57)
mandate premium dummy	-0.280^{***}	-0.272^{***}
	(-5.86)	(-6.20)
mandate premium in the previous month	0.473^{***}	0.502^{***}
	(6.75)	(7.75)
mandate premium outlier dummy		0.651^{***}
		(4.48)
constant	0.255^{*}	0.237^{*}
	(2.57)	(2.59)
Observations	122	122
R-squared	0.7881	0.8224
Adjusted R-squared	0.7558	0.7934

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Among the variables, only the mandate premium dummy, the lagged dependent variable (the mandate premium in the previous month), and the outlier dummy are significant factors. A joint F-test of the monthly dummies reports we cannot reject the null hypothesis that all of the monthly dummy variables are zero. As a calculated value based on ethanol and gasoline prices, this lack of seasonal change in the mandate premium may hint the two prices have already included the seasonal change component of the mandate premium. As a result, this does not seem to cast more light onto the ethanol and gasoline price link.

3.2.2 The Link between Biodiesel and Diesel Prices

Similarly, the U.S. blend mandate and tax credit programs for biodiesel affect the price relationship between biodiesel and diesel. The two states of nature described above still hold.

The relationship between the price of biodiesel (P_{BD}) and diesel (P_D) also depends on which regime is binding. When a blend mandate requires consumers to use more biodiesel than they otherwise would in a free market, the blend mandate regime is binding and consumers will have to pay a higher price for biodiesel than the free market price. Under this regime, the price of fuel is a mixed average (Equation 3.2.2.1), where P_F refers to fuel (the mixture of biodiesel and diesel) price. The parameter α represents the fraction of biodiesel in a fixed volume of fuel. The price of biodiesel P_{BD} will go down if the price of diesel P_D goes up and vice versa.

$$P_F = \alpha P_{BD} + (1 - \alpha) P_D \qquad (3.2.2.1)$$

When consumers demand more biodiesel than EPA's annual requirement, the tax credit regime is expected to be binding as P_{BD} and P_D are locked onto each other as fuel substitutes. Equation 3.2.2.2 models the minimum price of biodiesel when it competes with diesel as a substitute, where t_d is the diesel fuel tax and λ (=0.913) refers to the fractional mileage a gallon of biodiesel can obtain compared to a gallon of diesel. With a positive blender's tax credit (t_c), the lowest biodiesel prices can go is given by Equation 3.2.2.2'.

$$P_{BD}^{*} = \lambda P_D - (1-\lambda)t_d \qquad (3.2.2.2)$$

$$P_{BD}^{*} = \lambda P_D - (1-\lambda)t_d + t_c \qquad (3.2.2.2')$$

Under the framework of these two regimes, we now examine the relationship between the diesel price P_D and the biodiesel price P_{BD}. We first predict the lowest biodiesel prices can go P_{BD}^{*} using Equation 3.2.2.2', and then take the difference between P_{BD} and P_{BD}^{*} to derive the mandate premium. In theory, when the mandate premium is high, the blend mandate regime is binding and consumers will have to pay a higher biodiesel price. As the biodiesel price under such circumstance does not reflect its real value as a fuel, P_{BD} and P_D become delinked. Alternatively, if the mandate premium is low, P_{BD} and P_D is closely linked under the tax credit regime.

Unlike ethanol price that switches between the two regimes, the blend mandate regime appears binding for biodiesel price most of the time throughout our data range as shown in Figures 3.2.2.1 (except briefly in 2014). Contrary to the relationship between ethanol and gasoline, Figure 3.2.2.2 shows biodiesel price has been consistently higher than the price of diesel throughout the data period despite its lower energy content. Under this circumstance, we test the hypothesis of the correlation between P_{BD} and P_D will go down as the mandate premium goes up and Table 3.2.2.1 shows the results. The correlations between the two variables switch back and forth as the mandate premium increases and we cannot arrive at a conclusion about our theory's prediction.

Table 3.2.2.1 Correlations between Biodiesel and Diesel Prices

Mandate Premium	No. of Observations	Correlation
Full Sample	117	0.8402
Observations above the First Quartile	87	0.9039
Observations above the Median	58	0.8850
Observations above the Second Quartile	57	0.8850
Observations above the Third Quartile	29	0.8955

Alternatively, we examine the trends of percentage change in prices of the two fuels. Under the mandate binding regime, we would predict percentage change in the prices of biodiesel and diesel would travel in opposite directions. However, as shown in Figure 3.2.2.3, the general trends of the two variables actually walk together most of the time except briefly in Q1 of 2010, Q4 of 2011, Q4 of 2012, Q2 of 2013, and Q4 of 2016. There are many possible causes for the divergence. For example, if a group of major refinery plants undergoes prolonged period of maintenance in the spring, diesel price will go up with reduced overall production and biodiesel may be forced to be sold at a lower price with its normal production level due to the shortage in diesel supply for blending. Alternatively, if there is an exchange rate crisis with a trade partner's currency, U.S. may acquire less biofuels through import to meet its annual RFS blend goal, putting more pressure on domestic biodiesel producers and driving up biodiesel price. Meanwhile, if it is a busy summer driving season and more gasoline is produced by refineries than diesel from a barrel of oil due to the price premium, diesel price can be low. This is what explains the divergence in price change trends in 2011 and 2013. Though domestic biodiesel plants had excess capacities, the blend mandate's structure of RFS prevented the producers from capturing the excess profit in the market as import of Brazilian ethanol fell due to

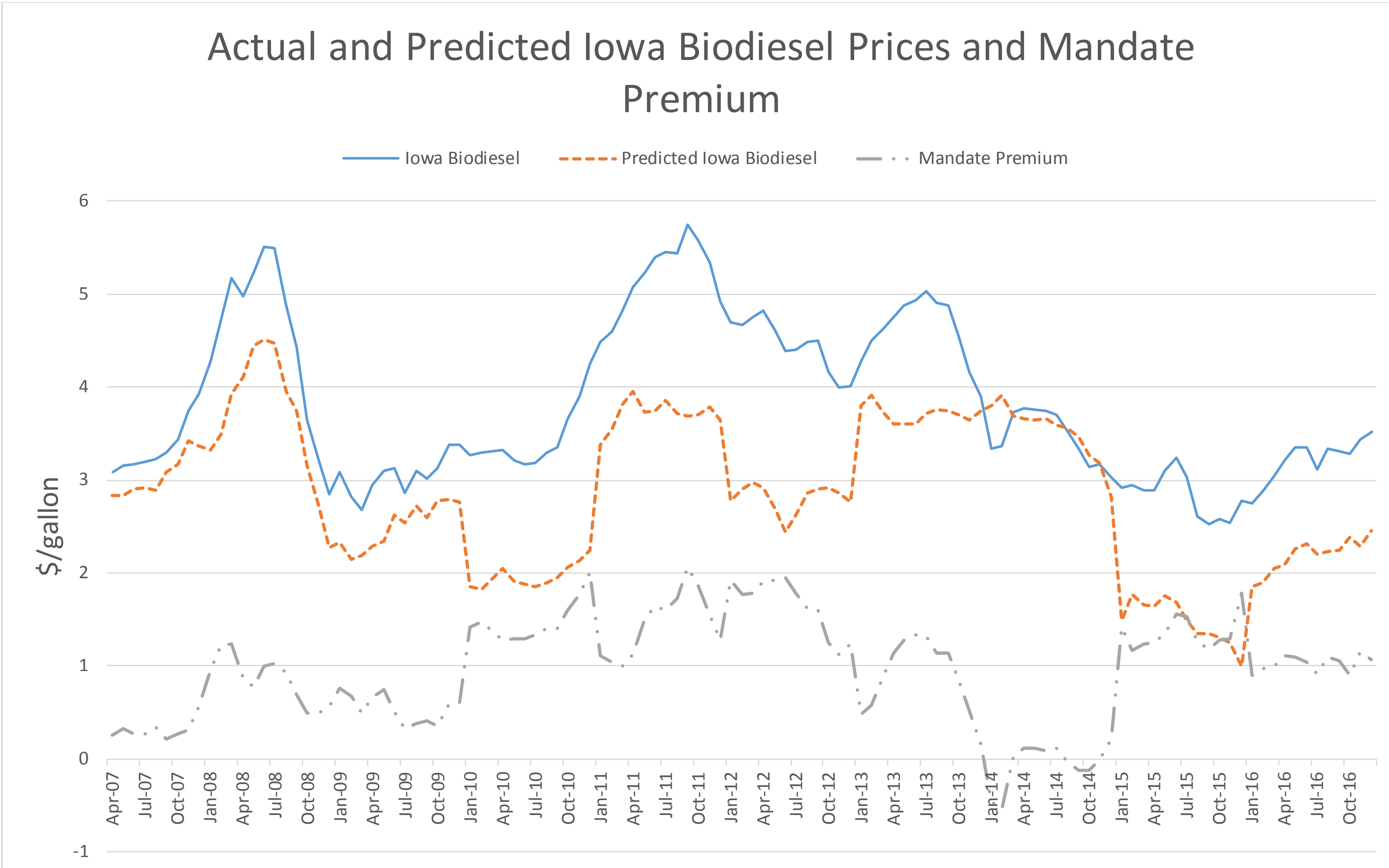

Figure 3.2.2.1 Actual and Predicted Biodiesel Price and Mandate Premium

Source: Biodiesel Price, Historical Biodiesel Operating Margins, CARD, ISU

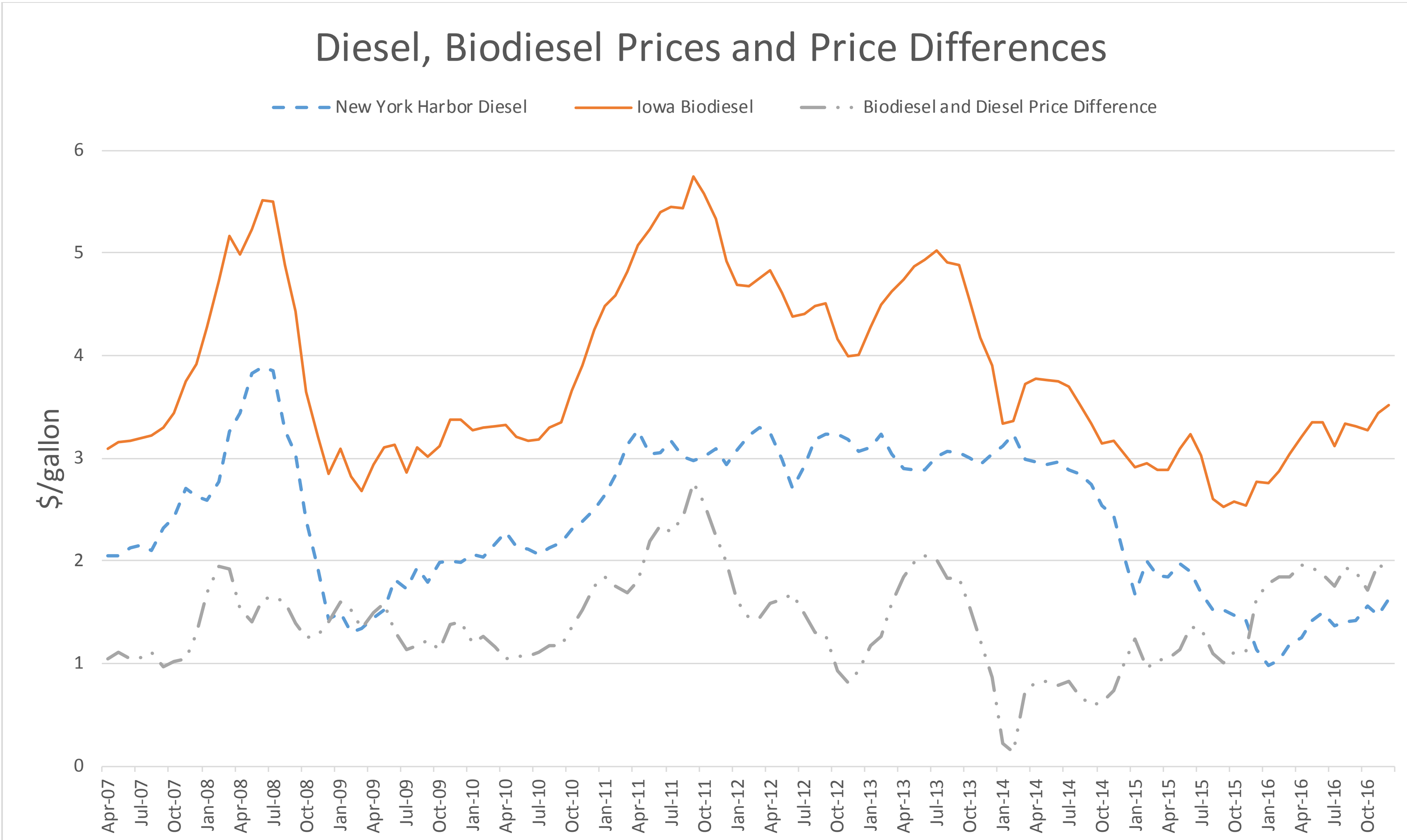

Figure 3.2.2.2 Diesel and Biodiesel Prices and Price Difference

Source: Biodiesel Price, Historical Biodiesel Operating Margins, CARD, ISU

New York Harbor Ultra-Low Sulfur No 2 Diesel Spot Price (Dollars per Gallon), Monthly, EIA

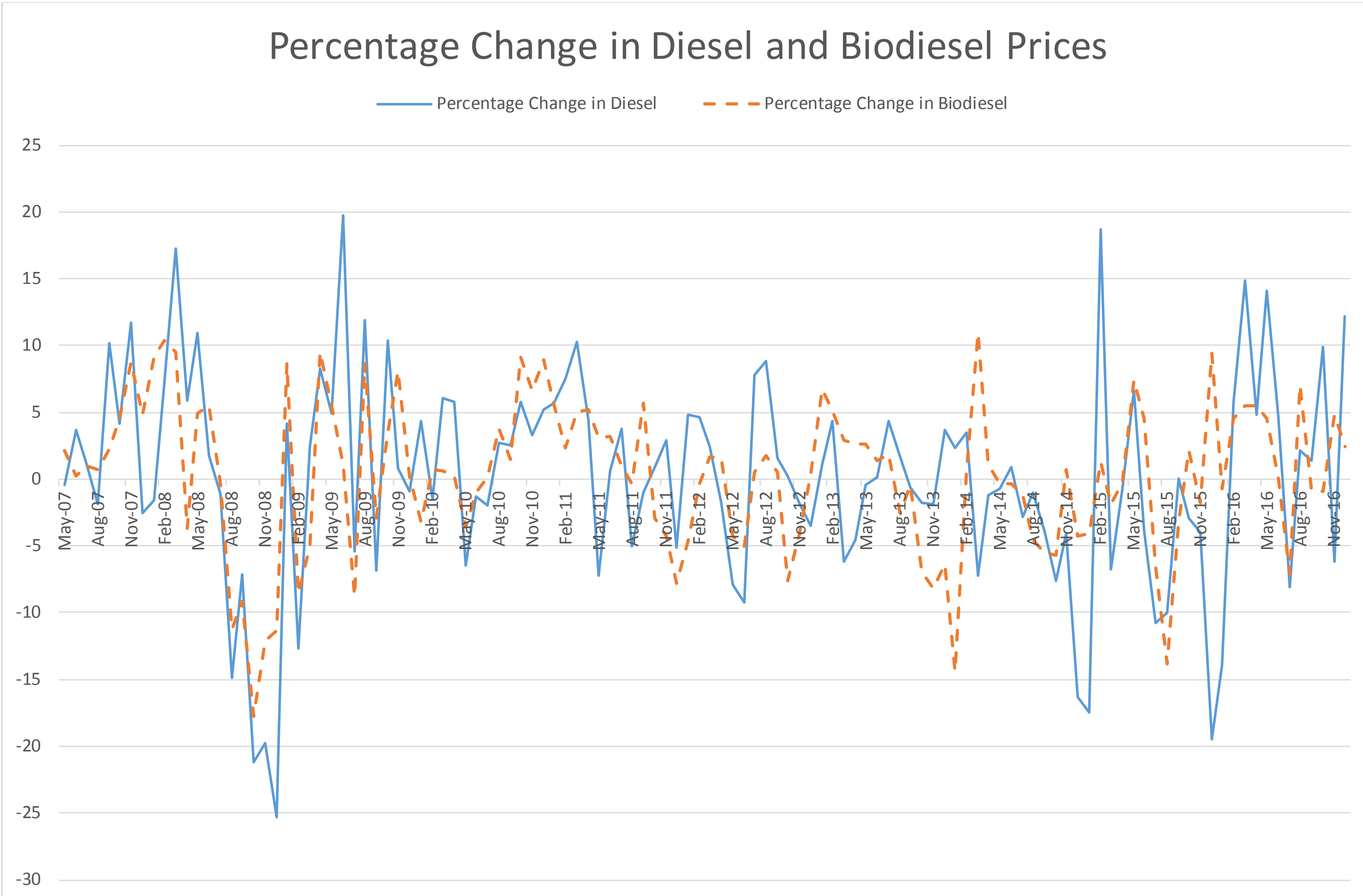

Figure 3.2.2.3 Percentage Change in Diesel and Biodiesel Prices

exchange rate jump and domestically produced biodiesel was called upon to fill the gap (de Gorter, Drabik, and Just, 2015).

The limitation of trying to use the reduced form model in Equation 3.2.2.2' to study the interaction between biodiesel and diesel prices is that it is not as robust and effective as a large structural model, which could handle controlling of other factors more effectively. However, this simple model has its own merit in showing us the different possible causes for the divergence in the two prices within the framework of the two states of nature.

3.3 The Link between Crops and Biofuels Prices

The beginning of the biofuel era has directly affected crop production in the United States. As the primary feedstock of ethanol, plants has been using 35 to 40 percent of the corn crop every year recently (USDA, 2016). Grains and oilseeds, particularly corn and soybean, make up the bulk of crop values in the four states of large crop sales (Iowa, Illinois, Minnesota, and Nebraska) (USDA, 2016). As showed in Figure 3.3.0.1, soybean production has also picked up with the hike in corn output. The newly created crop and biofuel price links become ever important.

3.3.1 The Link between Corn and Ethanol Prices

Corn has long been used for both human consumption and animal feed and the beginning of the US biofuel era in 2006 added extra value to the crop. As the main feedstock for ethanol, corn yields the co-product distiller's dried grains with soluble (DDGS), a common animal feed, and facilities could process DDGS further to obtain corn oil suitable for both human consumption and biodiesel with investment in production facilities. Based upon these facts and current technology, we model the corn and ethanol price links in Equation 3.3.1.1.

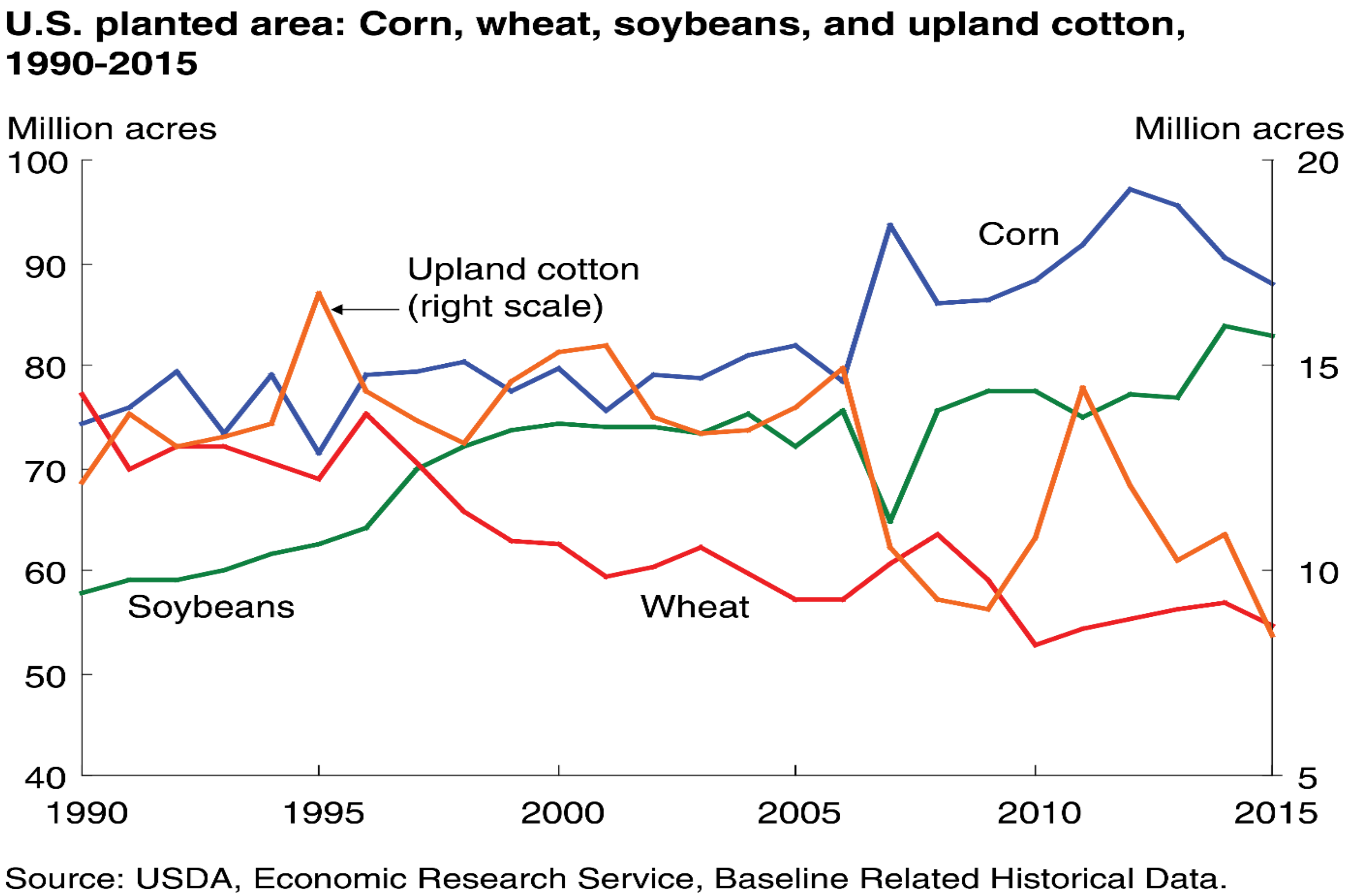

Figure 3.3.0.1 U.S. Major Corp Products Acreage Information

$$P_C^* = \frac{\beta}{1-r\gamma} * (P_E - c_o) + \frac{\theta}{1-r\gamma} * P_{CO} \text{ (3.3.1.1)}$$

P_C^* is the predicted price of a bushel of corn given the prices of P_E (ethanol price per gallon), c_o (ethanol production cost per gallon), and P_{CO} (corn oil price per pound). β, which equals 2.8, is the gallons of ethanol per bushel of corn yields. r is the relative price of DDGs and corn. γ is the bushel of DDGS obtained after the crush and has the value of 0.304. And θ is the pounds of corn oil obtained from a bushel of corn, which usually equals 0.5. de Gorter, Drabik, and Just provided all the technical coefficients (2015).

Equation 3.3.1.1 assumes a zero profit condition (though we recognize the ethanol market was not mature in its early years). In a perfectly competitive market, an ethanol producer will monitor its production such that the revenue it earns from producing the last unit of output should equal to the unit's cost. Under this assumption, an over-prediction of corn price would mean an ethanol producer will benefit from the lower actual corn price, earning positive profit. On the other hand, if the predicted price is lower than the actual price, ethanol producers will earn negative profit.

Though either positive or negative profits may seem abnormal once a market matures, there are different possible reasons for their occurrences. During the early years of the mass production of biofuel, producers might face capacity constraints as they continued to expand their operation to capture economies of size. Within this scenario, producers use less corn than the optimal level and enjoy positive profit on the last sold unit and corn price would not be bid up. Meanwhile, though less likely, the gasoline supply chain might also need time to adjust their marketing channels to accommodate the sudden influx of large amount of fuel ethanol, causing their profit to deviate from the normal level.

However, such positive or negative profit periods should be transient. When facing positive profit on the last unit, producers will attempt to capture more profit with production expansion. When facing negative profit, producers, in theory, will keep the facilities running to cover the variable cost but eventually will shut down if they keep losing money.

Figure 3.3.1.1 shows the actual and predicted corn prices together with prediction errors based on the model. Overall, the predicted corn prices have not been lower than the actual corn price, meaning ethanol producers made positive profits, except in late 2008 to mid-2009, the first half of 2012, late 2012 to the first quarter of 2013 and late 2015 to the first quarter of 2016. Meanwhile, predicted corn price has been consistently higher than the actual corn price between 2006 and 2008, the last quarter of 2009 to the first quarter of 2010, August 2010 to the end of 2011, February 2013 and January 2015, and April 2016 till the year's end.

We investigate ethanol producers' profits, the differences between the actual corn prices and the predicted corn prices (3.3.1.1) with Model 3.3.1.1. For all profit below 0 (meaning the actual corn price is lower than the predicted corn price), the profit dummy will be 1.

$$\Pi_t = f(intercept, linear\ trend, quadratic\ trend, monthly\ dummies, profit\ dummy, \Pi_{t-1}, outlier\ dummy, error) \quad (3.3.1.1)$$

We first examine the profit. Table 3.3.1.1 shows there are two outliers whose values are three standard deviations away from the mean. The two observations occurred in March and April of 2014.

Table 3.3.1.1 Outliers of the Ethanol Plant Profit

Variable	Obs	Mean	Std. Dev.	Min	Max
pe_corn	120	0.6337337	1.066621	-0.8643347	5.499552

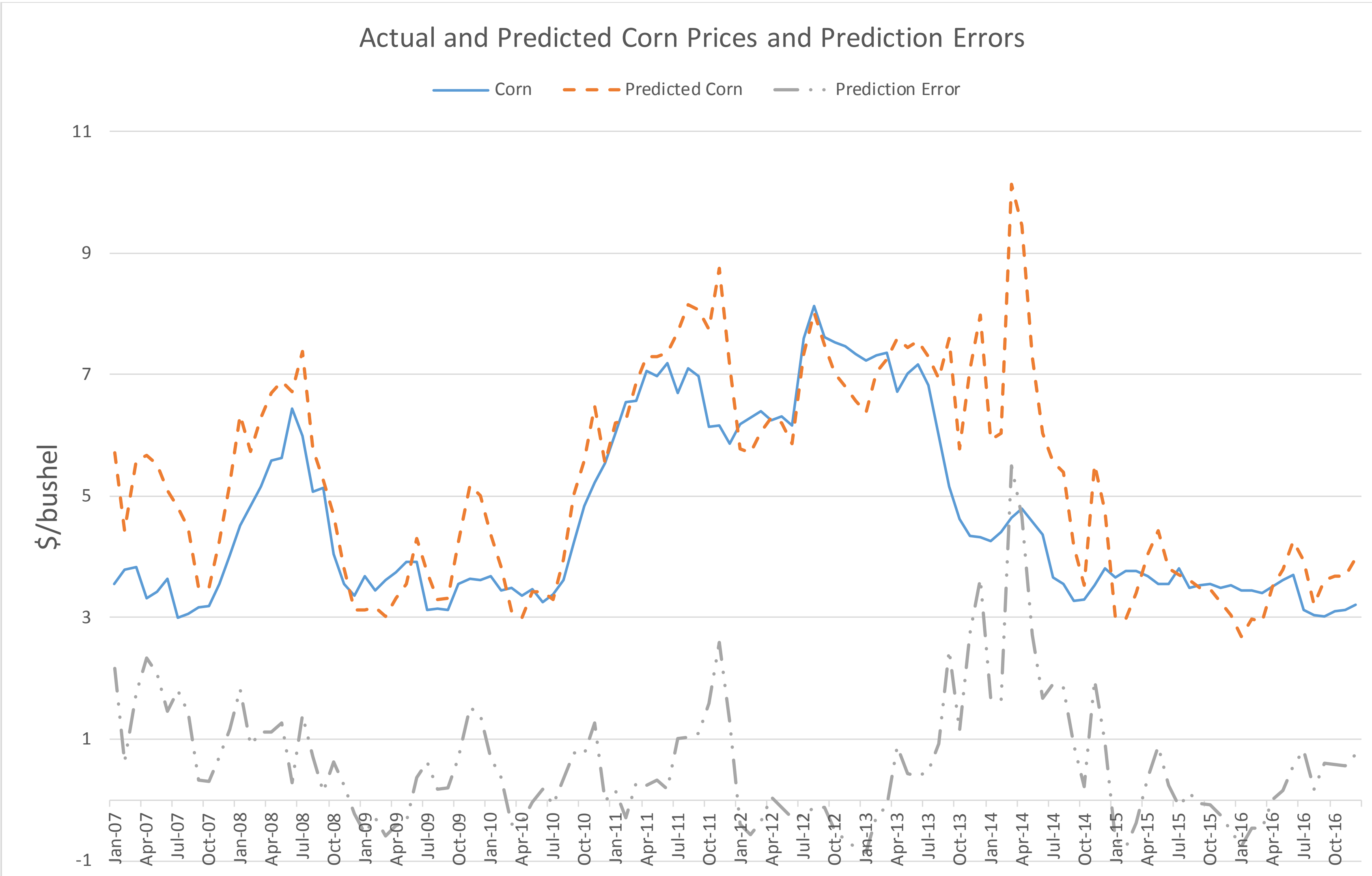

Figure 3.3.1.1 Actual and Predicted Corn Prices and Prediction Errors

Source: Corn Price, Historical Ethanol Operating Margins, CARD, ISU

After dropping the two observations, we run an OLS regression to predict the profit margin and try to detect any outlier again based on the prediction errors. We detect two more outliers and give them both a dummy and run the regression again. The results of both regressions are shown in Table 3.3.1.3.

Table 3.3.1.2 Outliers of the Ethanol Plant Profit Prediction Error

Variable	Obs	Mean	Std. Dev.	Min	Max
pe_corn_d	117	-7.52e-10	0.4599968	-1.025543	1.720166

The results we get are similar to the ethanol and gasoline model. An F test of the joint significance of the monthly dummies shows we cannot reject the null hypothesis of all the monthly dummy coefficients are zero. The lagged profit term from the previous month, the profit dummy, and the prediction error outliers are all significant in this case.

3.3.2 The Link between Soybean and Biodiesel Prices

As mentioned in Chapter 2, despite biodiesel production sources from various feedstocks, soybean oil is the most common input for biodiesel manufacturing in the U.S. We will use soybean to complete our analysis of the crop and biofuel price links.

The price relationships between corn and ethanol and soybean oil and biodiesel differ. The processing of corn yields ethanol, DDGS, and corn oil. DDGS is an important animal feed and ethanol producers return it to the market almost as a corn equivalent. With this fact, ethanol production increase causes minimal change in the supply of corn, and we call DDGs a co-product of corn processing. Unlike corn or DDGs, farmers do not usually feed soybean to animals directly due to soybean storage problem and animal health concern (Lane, 2000). Instead, soybean processors often crush soybean to obtain soybean oil and soybean meal, the

Table 3.3.1.3 Regression of Ethanol Producer Profits

	(1) Producer Profit	(2) Producer Profit
linear trend	0.00325	-0.00102
	(0.58)	(-0.21)
quadratic trend	-0.0000256	0.00000303
	(-0.58)	(0.08)
January	-0.375	-0.199
	(-1.65)	(-0.99)
February	-0.155	-0.00853
	(-0.69)	(-0.04)
March	0.121	0.247
	(0.51)	(1.20)
April	0.133	0.279
	(0.57)	(1.35)
May	-0.0210	0.160
	(-0.09)	(0.82)
June	-0.331	-0.148
	(-1.46)	(-0.74)
July	0.195	0.363
	(0.87)	(1.83)
August	-0.184	0.00151
	(-0.81)	(0.01)
September	-0.0878	-0.0973
	(-0.39)	(-0.50)
October	-0.175	0.00361
	(-0.78)	(0.02)
November	0.415	0.591^{**}
	(1.83)	(2.96)
prediction error negative dummy	-0.788^{***}	-0.752^{***}
	(-6.02)	(-6.58)
prediction error of the previous month	0.497^{***}	0.461^{***}
	(8.29)	(8.75)
prediction error outlier dummy		1.886^{***}
		(5.75)
constant	0.477^{*}	0.436^{*}
	(2.05)	(2.15)
Observations	117	117
R-squared	0.7337	
Adjusted R-squared	0.6941	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

latter an important feed. Within this process, soybean meal is not returned to the market as a soybean equivalent. The production of more biodiesel from soybean oil leads to the crushing of more soybean, and the supply of soybean meal in the market will increase, driving down soybean meal price if demand remains unchanged. For this reason, we call soybean meal a joint product of soybean crushing.

Based upon the main usage of soybean besides human consumption, our model describes the soybean (P_{SB}) and biodiesel (P_B) price links in the following two equations, where P_{SB} refers to the price of a bushel of soybean.

$$P_{SB}^{*} = \beta_1 * P_{SO} + \beta_2 * P_{SM} - \beta_1 * C_{0sb} \quad (3.3.2.1)$$

$$P_{SO}^{*} = \beta_3 * (P_B - C_{0b}) \; (3.3.2.2)$$

According to de Gorter, Drabik, and Just, every bushel (60 pounds) of soybean yields 11.28 pounds (β_1) of soybean oil and 48.72 pounds (β_2) of soybean meal after crushing (2015). One pound of non-consumable soybean oil yields 0.13 gallons (β_3) of biodiesel. C_{0sb} is the processing cost of one pound of soybean oil and C_{0b} is the processing cost of a gallon of biodiesel. For both variables, we assume soybean and biodiesel processers operate under constant return to scale and their values are fixed. Lastly, P_{SO} and P_{SM} each denotes the prices of one pound of soybean oil and one pound of soybean meal.

We first show the trends of biodiesel, soybean oil, and soybean prices in Figure 3.3.2.1a/b/c to illustrate the necessity of using two equations to model the relationships. Unlike the tight price link between ethanol and corn, the price of biodiesel is not closely linked to soybean price due to the intermediate channel of soybean oil. Biodiesel and soybean oil prices track each other most of the time in Figure 3.3.2.1a except in 2011 and the price trends of soybean oil and soybean are similar in Figure 3.3.2.1b except in 2009, 2010, and 2016. However, biodiesel and soybean prices mostly walked in opposite directions between 2009 and 2012 and between 2014 and 2015 in Figure 3.3.2.1c. Thus, the price link between soybean and biodiesel appears indirect and the two prices do not always move together.

$$P_{SB}^{*} = \beta_1 * P_{SO} + \beta_2 * P_{SM} \quad (3.3.2.1')$$

Although we do not have enough information about C_{0sb} from Equation 3.3.2.1, we can use Equation 3.3.2.1' to test the prediction power of our model under the assumption of processing costs with constant returns to scale. While QUALISOY, a soybean industry source, reports soybean crushing plants' average total cost and variable cost to be between 60 to 70 cents and 30 cents per bushel respectively in May, 2016, we do not have monthly processing cost data between 2007 and 2016 (Galloway, 2016). However, Figure 3.3.2.2 shows the predicted soybean price tracks soybean price almost perfectly in the absence of the information of actual processing costs.

Moreover, using Equation 3.3.2.2, we obtain the predicted prices of soybean oil and Figure 3.3.2.3 shows the equation models the link between the two prices well except in 2011, 2013, and 2016. During these three years, the positive prediction errors mean biodiesel producers earn positive profit in the last unit produced. According to de Gorter, Drabik, and Just (2015), there was excess capacity in biodiesel production in the U.S. in 2011 and 2013. However, the nested US blend mandate prevented the plants from increasing their productions fast enough to eliminate the excess profit. Meanwhile, the unexpected increase in the biodiesel mandate in November, 2015 caused the excess profits of biodiesel producers in 2016.

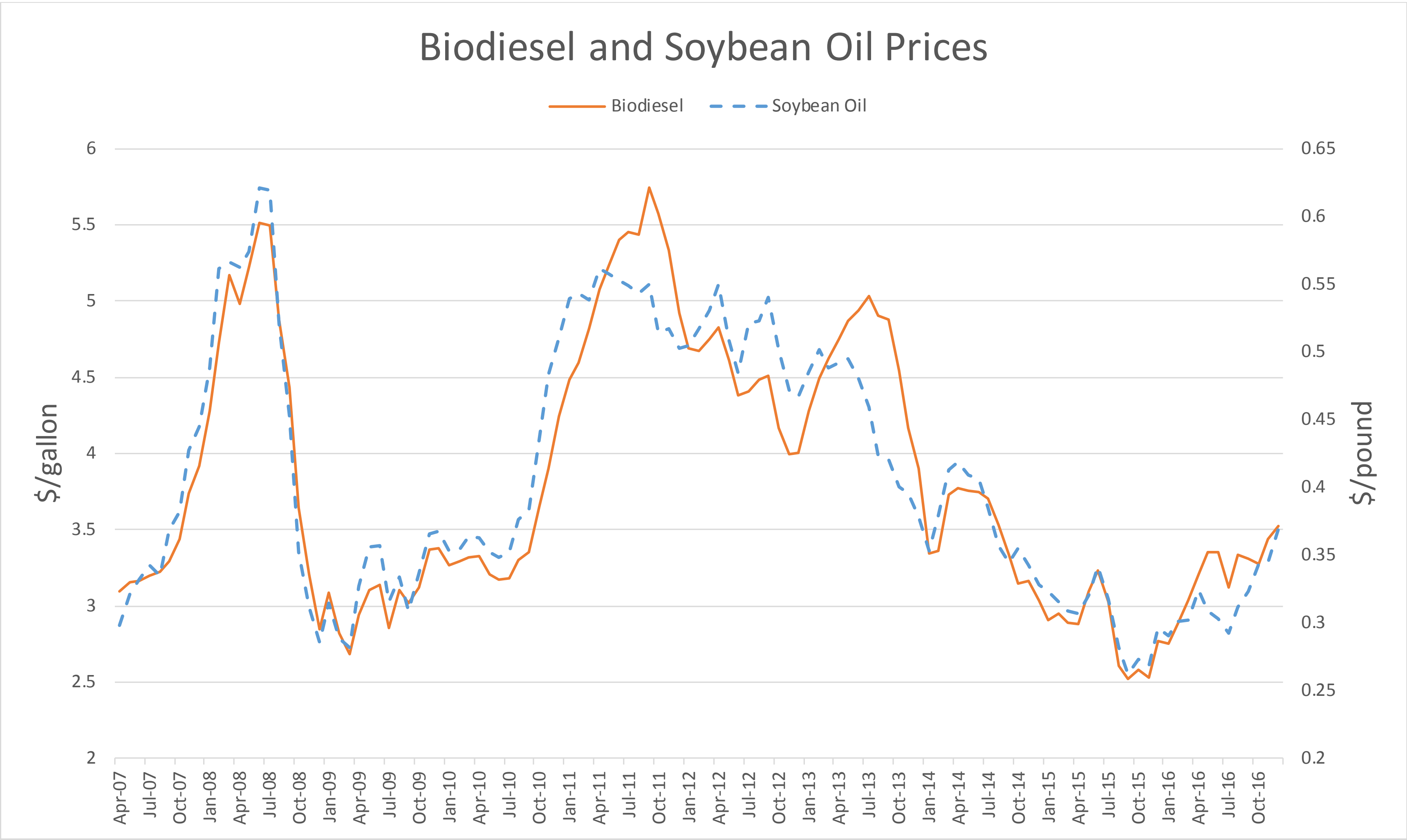

Figure 3.3.2.1a Biodiesel and Soybean Oil Price History

Source: Biodiesel Price, Historical Biodiesel Operating Margins, CARD, ISU

Soybean Oil Price, Biodiesel Weekly, CARD, ISU

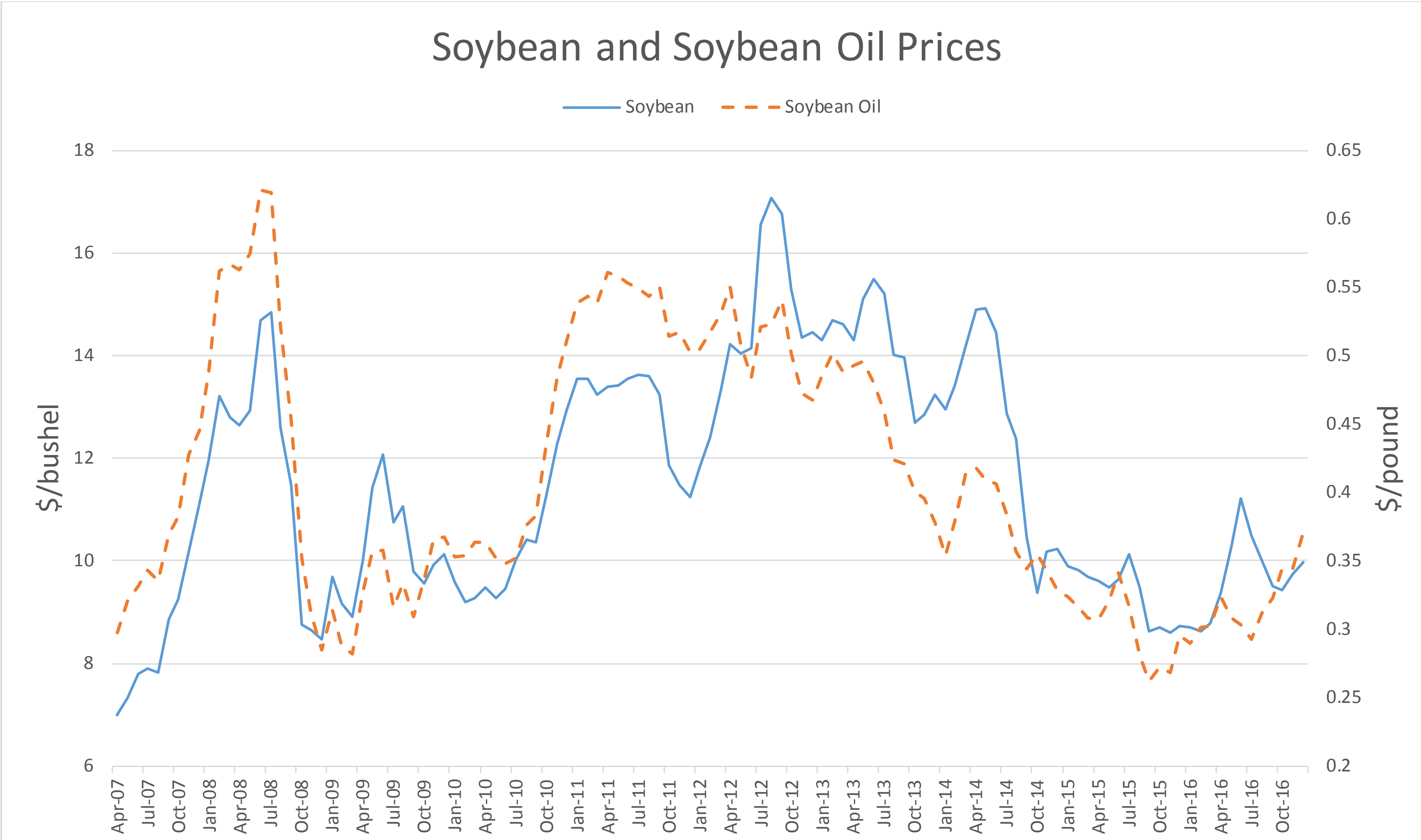

Figure 3.3.2.1b Soybean and Soybean Oil Price History

Source: Soybeans, Number 1 Yellow USD / Bushel; USDA, Daily, Datastream

Soybean Oil Price, Biodiesel Weekly, CARD, ISU

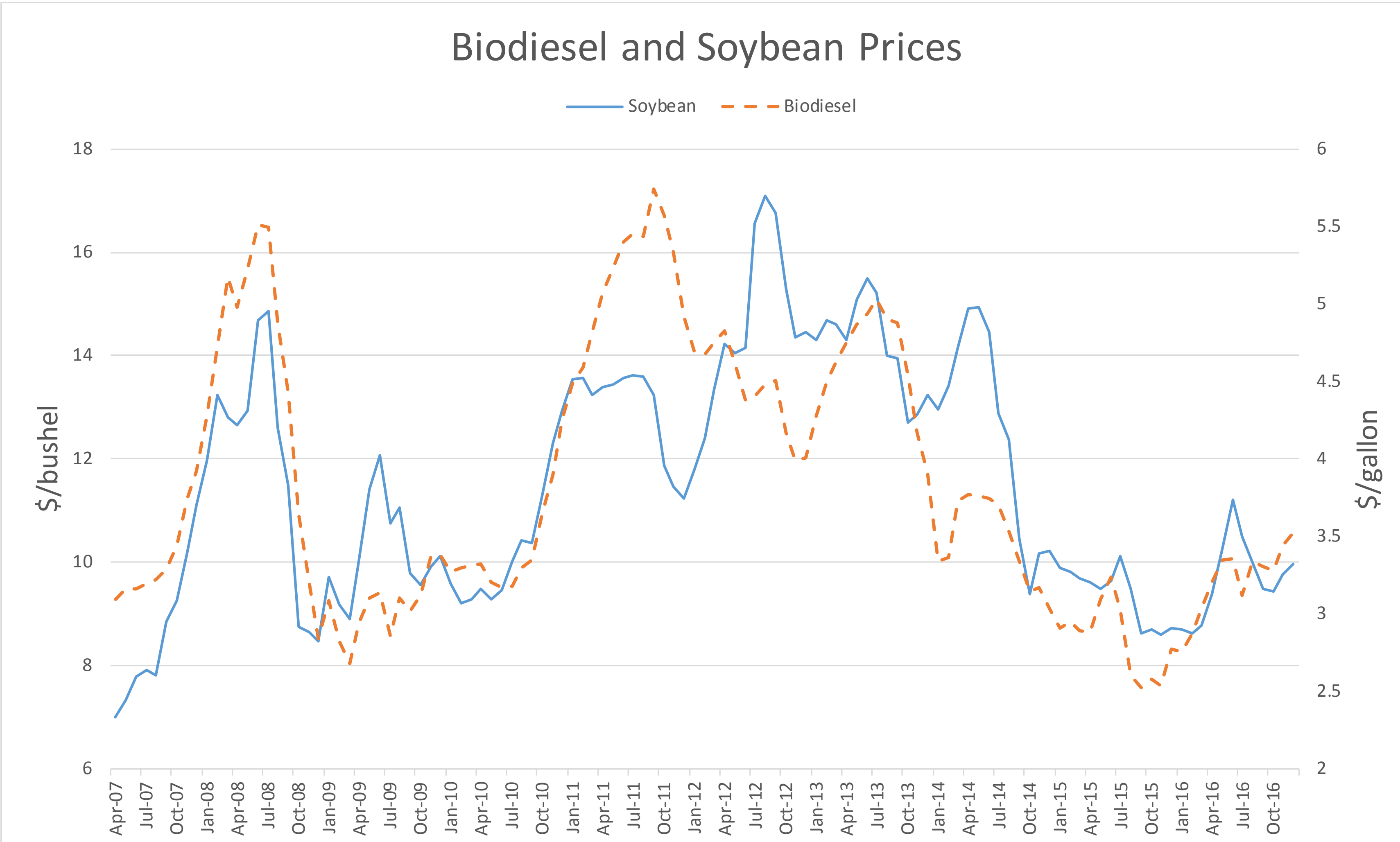

Figure 3.3.2.1c Biodiesel and Soybean Price History

Source: Soybeans, Number 1 Yellow USD / Bushel; USDA, Daily, Datastream

Biodiesel Price, Historical Biodiesel Operating Margins, CARD, ISU

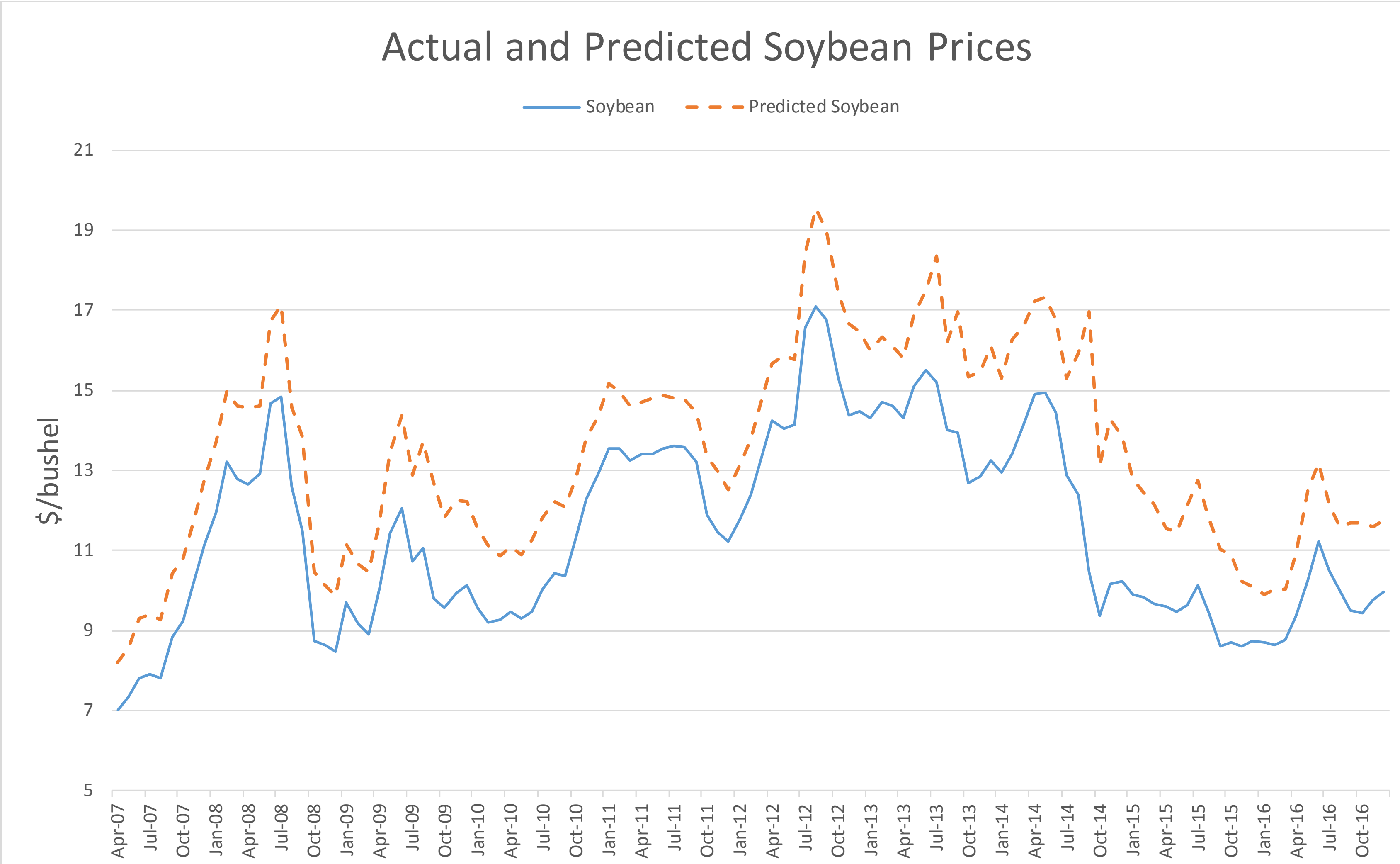

Figure 3.3.2.2 Predicted Soybean Price without Processing Cost and Actual Prices

Source: Soybeans, Number 1 Yellow USD / Bushel; USDA, Daily, Datastream

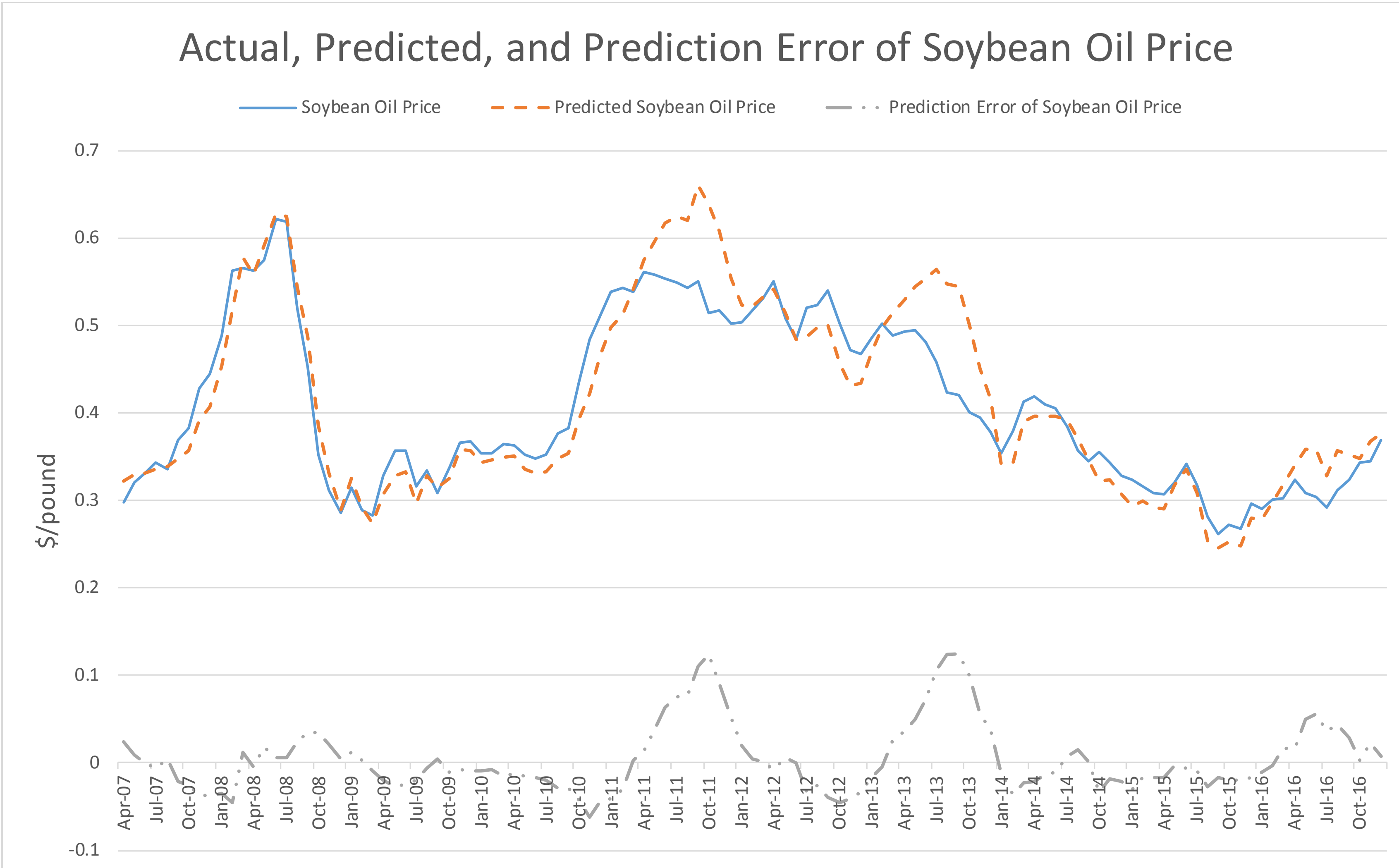

Figure 3.3.2.3 Actual and Predicted Soybean Oil Prices and Prediction Errors

Source: Soybean Oil Price, Biodiesel Weekly, CARD, ISU

In Chapter 3, we have constructed empirical models using the economic theories of the two states of nature from Chapter 2 to examine the price links between energy and crop commodities. We have found many factors that could explain the delinking of any price pairs. In Chapter 4, we will discuss using these relationships in simulations.

CHAPTER 4

SIMULATIONS OF ENERGY AND CROP PRICE LINKS

Building upon the economic theories and empirical models in previous chapters, we now explore how changes in policies and markets could influence commodity prices through energy and crop price links. We examine three scenarios in the following order: (1) what if the price of a barrel of crude oil stayed at $110 beginning January, 2008; (2) what if biofuel blenders' tax credit did not exist from the beginning; and (3) what if biofuel blenders' tax credit continued to exist throughout the data period.

4.1 When Crude Oil Price Increases

The energy and crop price links begin with crude oil. According to EIA, crude oil provided for 36 percent of U.S. total energy consumption in 2015 while the second major source natural gas contributed 29 percent (2017). The increase in the price of the major energy source since the early 2000s concerned policy makers as the RFS came into place in the mid-2000s. By the beginning of 2007, oil price was almost 60 dollars per barrel, compared to the average price in the 20s of early 2000s, and the price increase continued, reaching the maximum of 132.72 per barrel in July 2008 (Brent free-on-board spot crude oil price) before leveling off . However, the price hike came back again in 2011 and crude oil price maintained its level above 100 dollars per barrel for the next three years.

As shown in Figure 4.0.1, though crude oil price began its new round of increase in early 2007, 2008 was an important year with the sharp price increase within a few months. Thus, it would be of interest if we can simulate the scenario of crude oil price stayed at 110 per barrel (the average price in the first six months of 2008) for the next few years and examine its impact

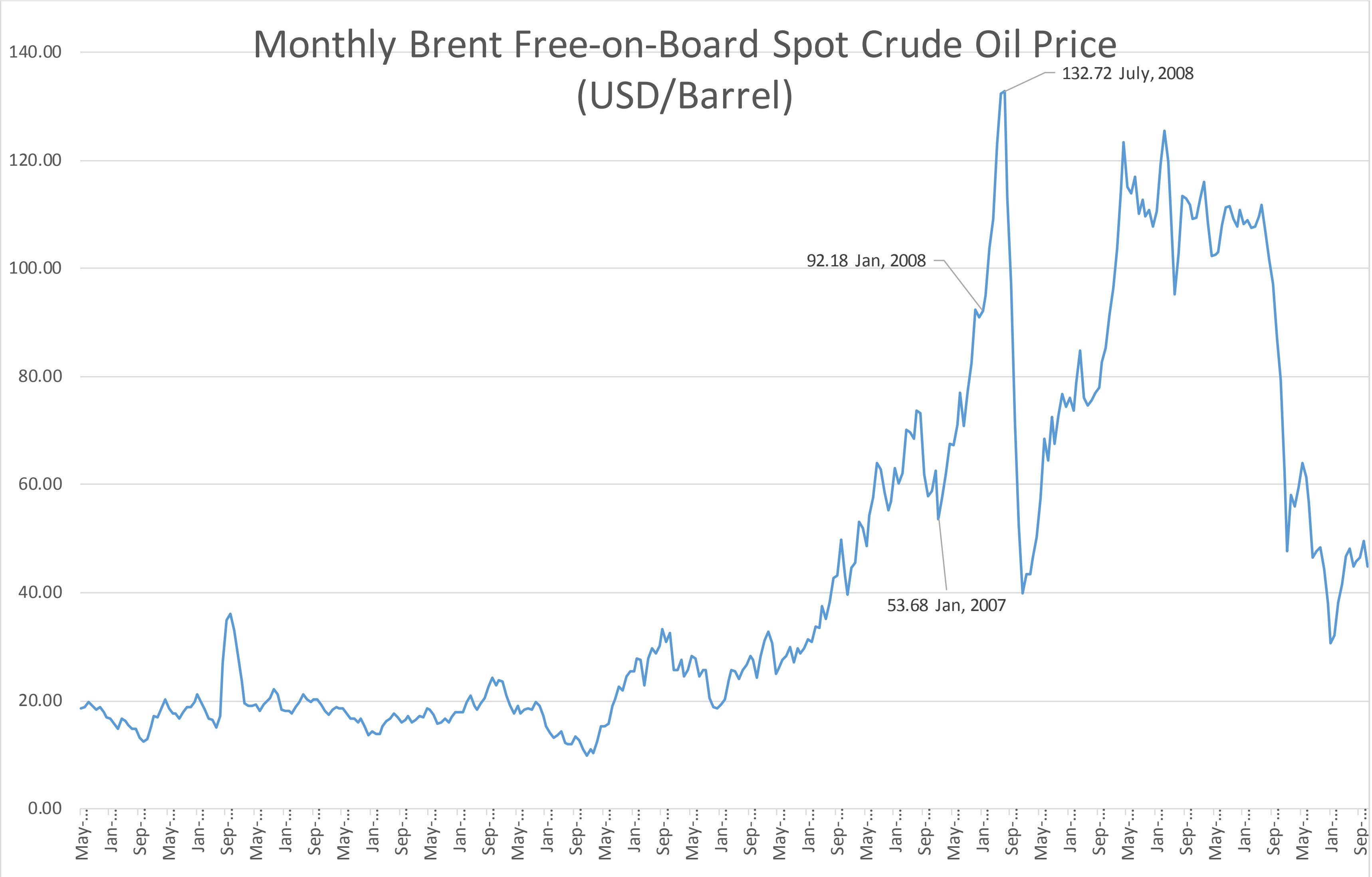

Figure 4.0.1 Monthly Brent Free-on-Board Spot Crude Oil Price (USD/Barrel)

Source: Europe Brent Spot Price FOB (Dollars per Barrel), Monthly, EIA on other commodity prices.

4.1.1 Crude Oil Price Increases and Corn Prices

To achieve this goal, we first predict the gasoline price beginning January, 2008 using Model 3.1.0.1, and then use the predicted gasoline price to calculate the predicted ethanol price using Equation 3.2.1.2. Lastly, we find the minimum corn price using Equation 3.3.1.1 based on the predicted ethanol price.

As shown in Figure 4.1.1.1, the simulated crude oil price is higher than its historical value except in May-August 2008, March-September 2011, November 2011, January-May 2012, August-October 2012, January-February 2013, August-September 2013, December 2013, and June 2014 (26 out of 95 months). In Figure 4.1.1.2, the price difference between simulated and historical gasoline prices follows the price difference trend in Figure 4.1.1.1 but otherwise differs in 11 months such that simulated gasoline price was higher than historical price even if the simulated crude oil price in that month was lower than the actual value. However, a closer look reveals only one of the 11 months (November 2011) has a price difference with an absolute value that is more than 5% of the average value of the simulated and historical gasoline prices. As prediction error can still occur despite the gasoline price model in Model 3.1.0.1 has an adjusted R-squared value of 0.9890, we can consider the price difference outlier to be the result of prediction errors when we cannot find an explanation from events in 2011. And, this single outlier will not disrupt the overall price pattern of the simulated gasoline price.

Figure 4.1.1.3 shows the predicted and historical ethanol prices. Compared to Figure 3.2.2.2, the predicted ethanol price is (by construction) overall higher than the historical ethanol price. As a result, the predicted ethanol price when crude oil stays at 110 dollars per barrel no longer tracks the trend of real ethanol price as well compared to its historical counterpart.

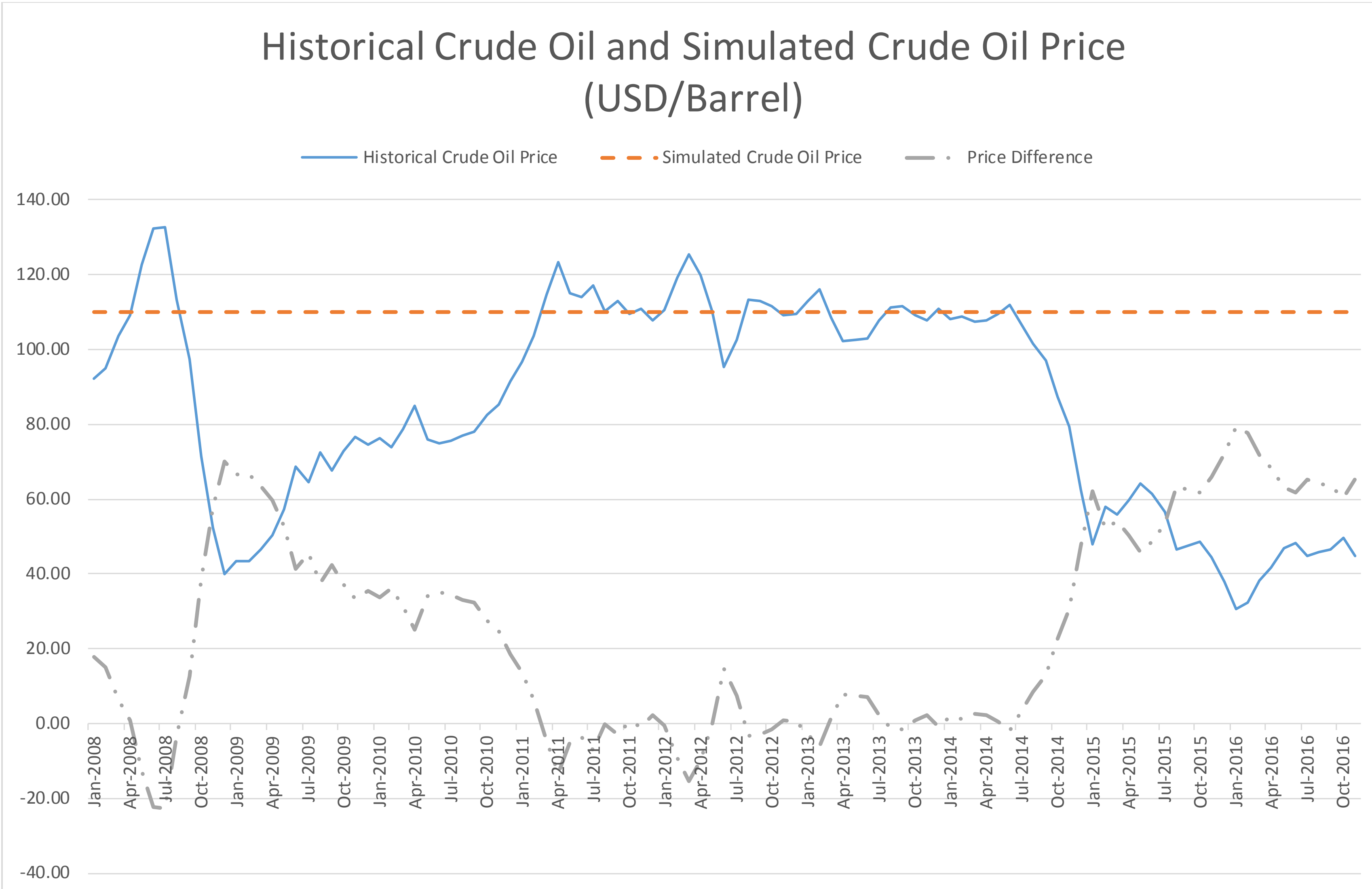

Figure 4.1.1.1 Historical Crude Oil and Simulated Crude Oil Price (USD/Barrel)

Source: Europe Brent Spot Price FOB (Dollars per Barrel), Monthly, EIA

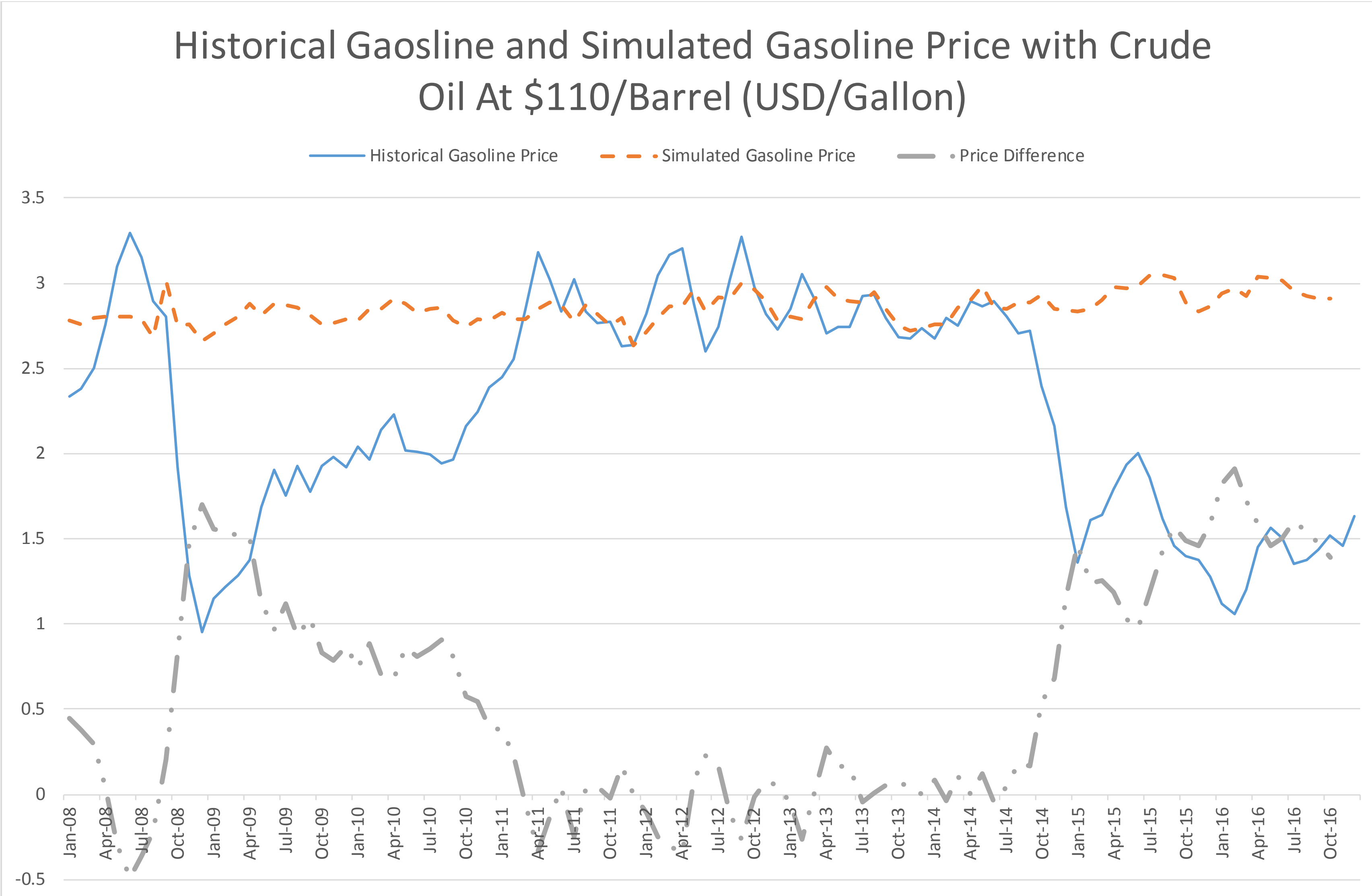

Figure 4.1.1.2 Historical Gasoline and Simulated Gasoline Price with Crude Oil at $110/Barrel (USD/Barrel)

Source: New York Harbor Conventional Gasoline Regular Spot Price FOB (Dollars per Gallon), Monthly, EIA

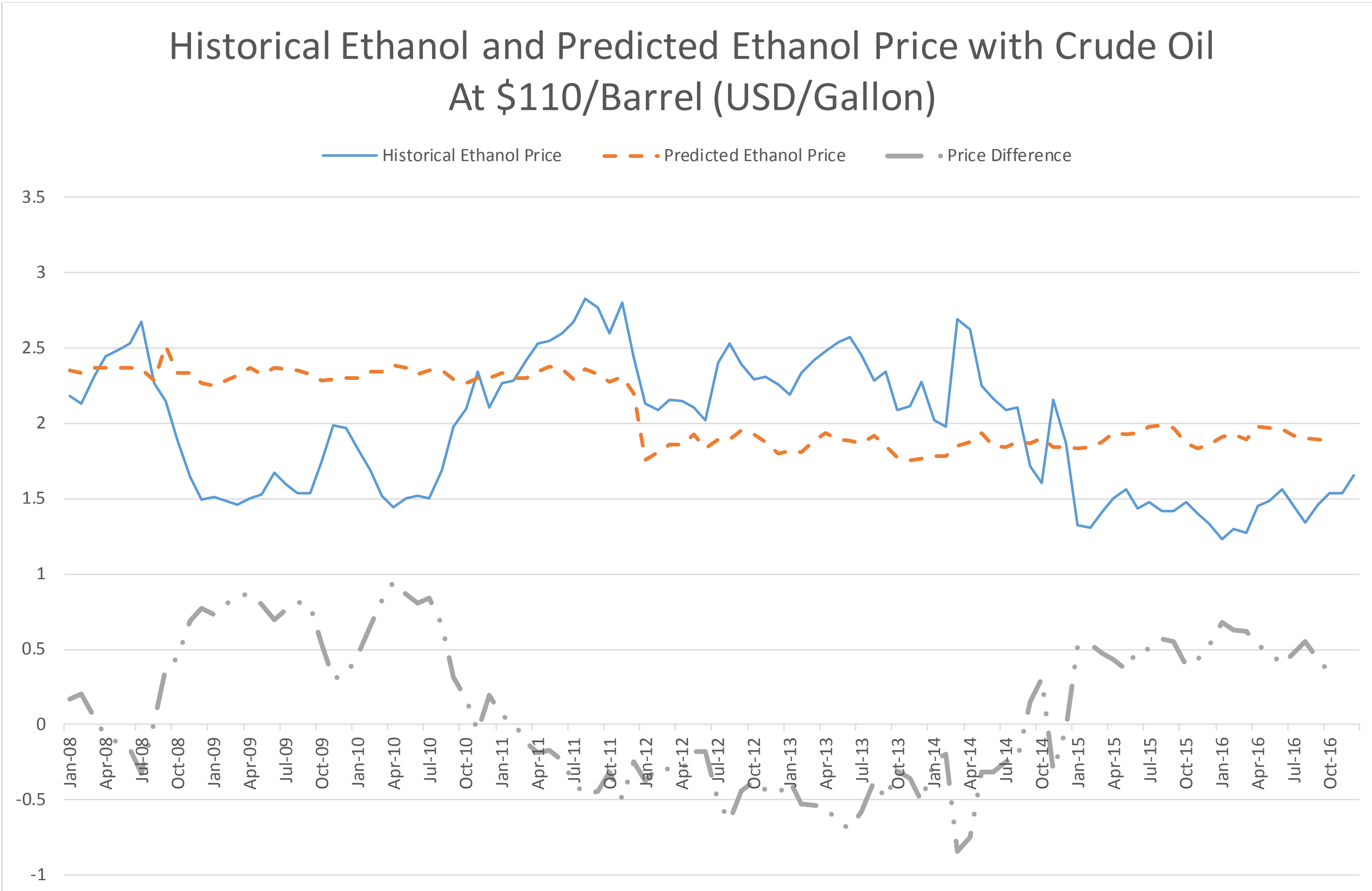

Figure 4.1.1.3 Historical Ethanol and Predicted Ethanol Price with Crude Oil at $110/Barrel (USD/Barrel)

Source: Ethanol Price, Historical Ethanol Operating Margins, CARD, ISU

However, the predicted ethanol price suggests ethanol price would have been higher between the second half of 2008 and 2010 and between the second half of 2014 and the end of 2016 if crude oil price stayed at 110 per barrel. This has to do with ethanol more likely to be a complement to gas during the two periods as its production capacity only reached the blend mandate's maximum cap in 2016. Meanwhile, as the average simulated gasoline price is lower between the second half of 2011 and the first half of 2014, historical ethanol price being higher than predicted ethanol price reflects this difference.

Due to the transmission through price link system in Figure 2.4.1, corn prices would have been higher between mid-2008 to 2010 and between the second half of 2014 and the end of 2016 as shown in Figure 4.1.1.4 if crude oil price stayed at 110 per barrel as we compare the scenario to what really happened in Figure 3.3.1.1. Meanwhile, a lower minimum corn price between the second half of 2011 and the first half of 2014 reflects the lower simulated gasoline price when compared to the actual. Overall, the corn price would have been more stable if the price of crude oil stays at 110 dollars per barrel from January 2008 onward.

4.1.2 Crude Oil Price Increases and Soybean Prices

To investigate the implication of high crude oil price on soybean prices, we first predict the diesel price beginning January, 2008 using Model 3.1.0.1, and then use the predicted diesel price to calculate the predicted biodiesel price using Equation 3.2.2.2'. Lastly, we find the minimum soybean price using Equation 3.3.2.1' based on the predicted biodiesel price. As we predict higher crude oil price will result in higher diesel and predicted biodiesel prices, we expect the crop market to crush more soybean for biodiesel production. This will lead to more soybean meal being available in the market, driving down its price. However, we assume the soybean meal prices in this simulation do not change from its historical values.

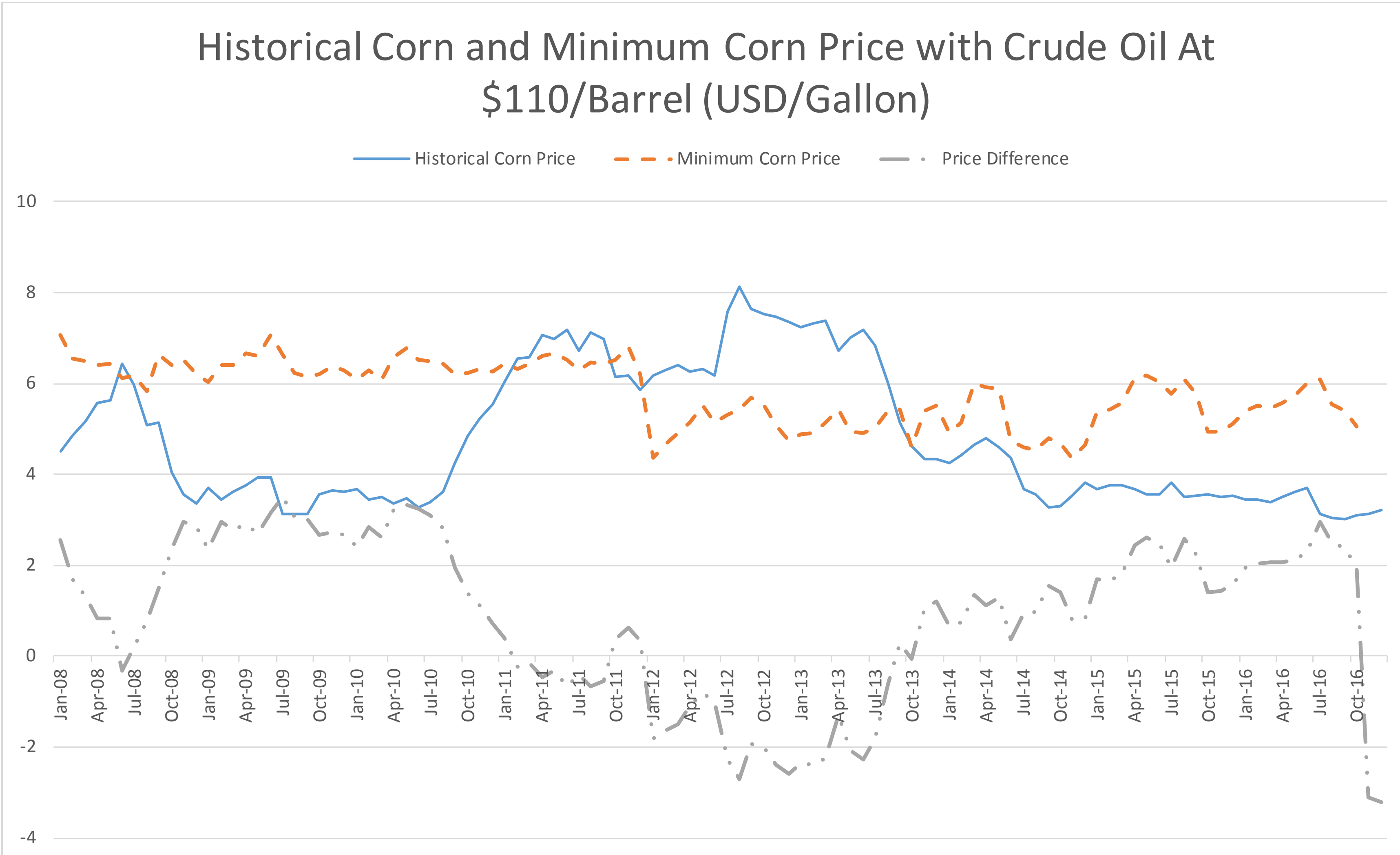

Figure 4.1.1.4 Historical Corn and Minimum Corn Price with Crude Oil at $110/Barrel (USD/Barrel)

Source: Corn Price, Historical Ethanol Operating Margins, CARD, ISU

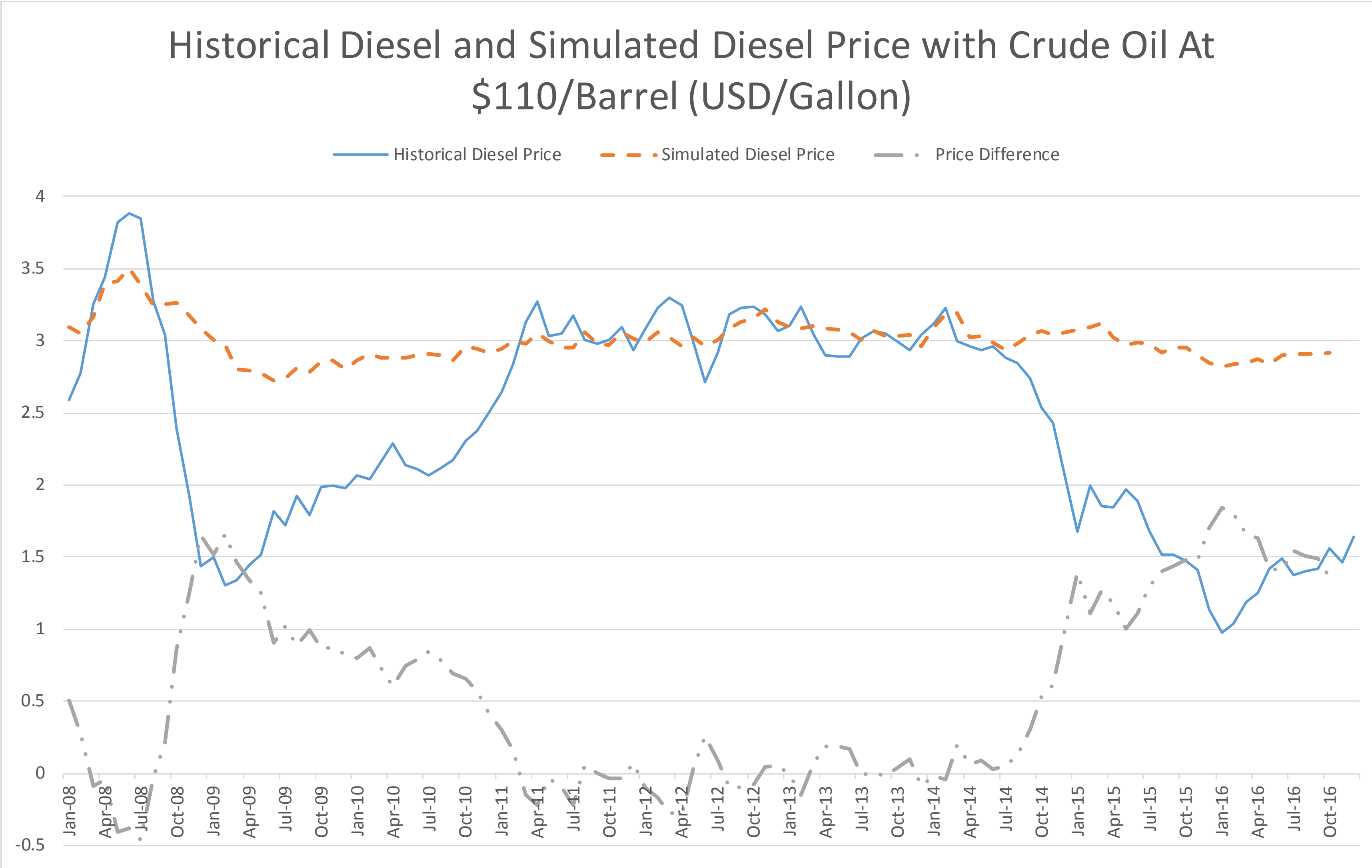

Figure 4.1.2.1 Historical Diesel and Simulated Diesel Price with Crude Oil at $110/Barrel (USD/Barrel)

Source: New York Harbor Ultra-Low Sulfur No 2 Diesel Spot Price (Dollars per Gallon), Monthly, EIA

Compared to the price difference trend in Figure 4.1.1.1, the price difference in Figure 4.1.2.1 deviates in 10 of the months. However, none of the deviations is more than 5% of the average value of the simulated and historical diesel price in any month. For similar reasons for the case of gasoline, we believe these minor deviations will not disrupt the overall price pattern of simulated diesel prices.

In Figure 4.1.2.2, the predicted biodiesel price does not provide a good prediction of the actual biodiesel price even after factoring in the absence of blenders' tax credit in the production years of 2010, 2012, and 2015. While the simulated diesel price is higher than the actual diesel price during the period between August 2008 and March 2011, the predicted biodiesel price does not follow the actual biodiesel price closely. The spurious production pattern of biodiesel in the early years in Figure 2.2.2, however, could help explain the poor prediction. Nevertheless, for the period between April 2011 and February 2014, the lower predicted biodiesel price due to the lower diesel price corresponds to a consistently higher actual biodiesel price. Lastly, as the biodiesel production picked up in 2014 onward, the predicted biodiesel price tracks the historical price slightly better in a period of high-simulated diesel prices compared to the actual prices.

Figure 4.1.2.3 shows the result of all the price transmissions reflected in soybean. Again, Equation 3.3.2.1' does not include the processing cost of crushing soybean into soybean meal and oil because we do not have the data. In addition, using a calculated average processing cost under the zero profit condition may bring more problems into the minimum price in this simulation scenario. Thus, processing costs are not removed and the minimum soybean price is consistently higher than the actual price except during the period between September 2010 and December 2012. Since the simulated diesel price between April 2011 and December 2012 is lower than the actual, it could account for part of the difference. Moreover, considering the

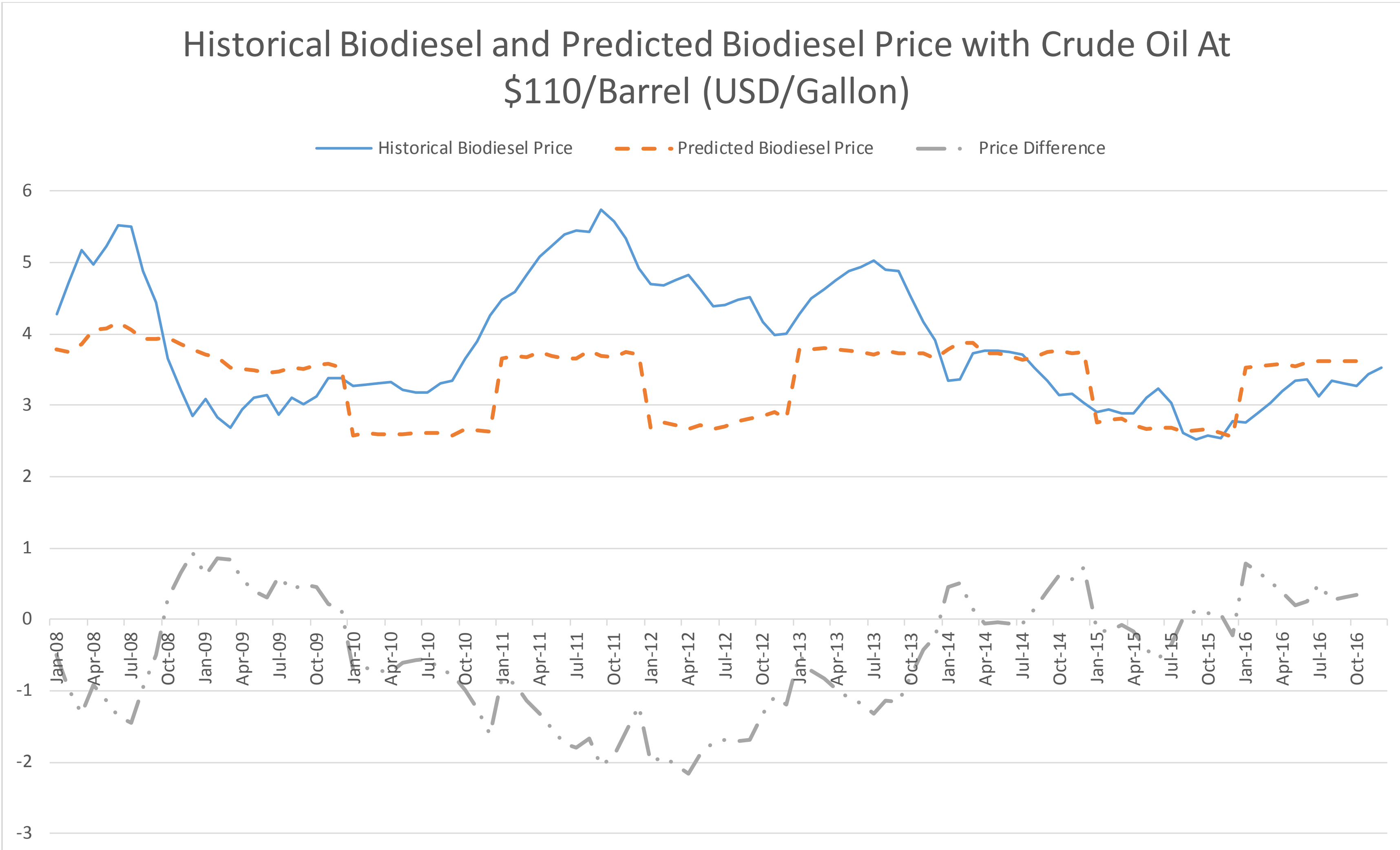

Figure 4.1.2.2 Historical Biodiesel and Predicted Biodiesel Price with Crude Oil at $110/Barrel (USD/Barrel)

Source: Biodiesel Price, Historical Biodiesel Operating Margins, CARD, ISU

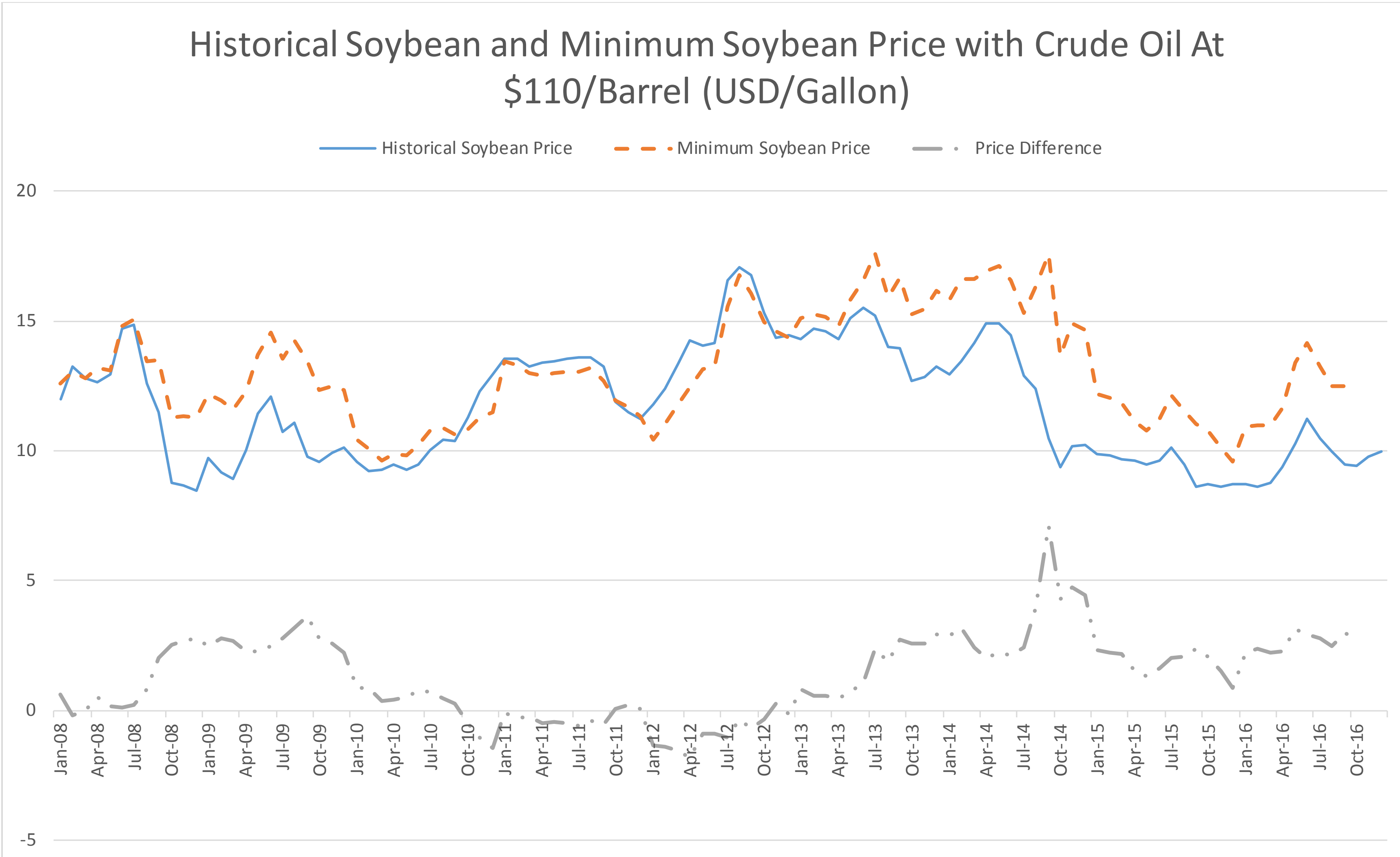

Figure 4.1.2.3 Historical Soybean and Minimum Soybean Price with Crude Oil at $110/Barrel (USD/Gallon)

Source: 48% Soybean Meal Truck Delivery Spot Price/Illinois (USD/short ton); USDA, Daily, Bloomberg

spurious biodiesel production pattern in the past few years and the mandate premium it has always had in its price, it is also very likely that the biodiesel industry has not matured to fully use the entire soybean share it should have to establish a tight price link between biodiesel and soybean.

4.2 When There Is No Blenders' Tax Credit

As mentioned in Chapter 2, the U.S. government uses biofuel blenders' tax credit and the biofuel blend mandate to support the industry among many other biofuel policies. In particular, the ethanol tax credit elapsed in 2012 while the biodiesel tax credit continues to exist but was allowed to elapse in 2010, 2012, and 2015 historically. In this simulation scenario, we investigate the implication of the removal of the tax credit on the prices of biofuels and crops. We assume no effects on energy and crude oil prices as we assume their supplies are exogenous.

Figure 4.2.1 predicts overall ethanol prices would be lower without the tax credit. The minimum ethanol price lies below the actual price throughout the data range except in September, 2014 with the minimum price being 4 cents higher than the actual one. In a competitive market where consumers are required to consume ethanol, ethanol retailers and blenders will lower the price when the tax credit is no longer available.

In comparison, the price of corn without blenders' tax credit in Figure 4.2.2 has more deviations. Since we link ethanol with corn prices in our model in Chapter 3, over-predictions and under-predictions of corn price can result from ethanol production capacity constraints. When we have over-predictions of corn price, ethanol producers earn positive profit and under-predictions signal negative profit. For the brief period at the end of 2008 and the beginning of 2009, minimum corn price falls below 0. If this would ever occur, owners would have stocked the corn to wait for a higher price in the ethanol market later among many other options.

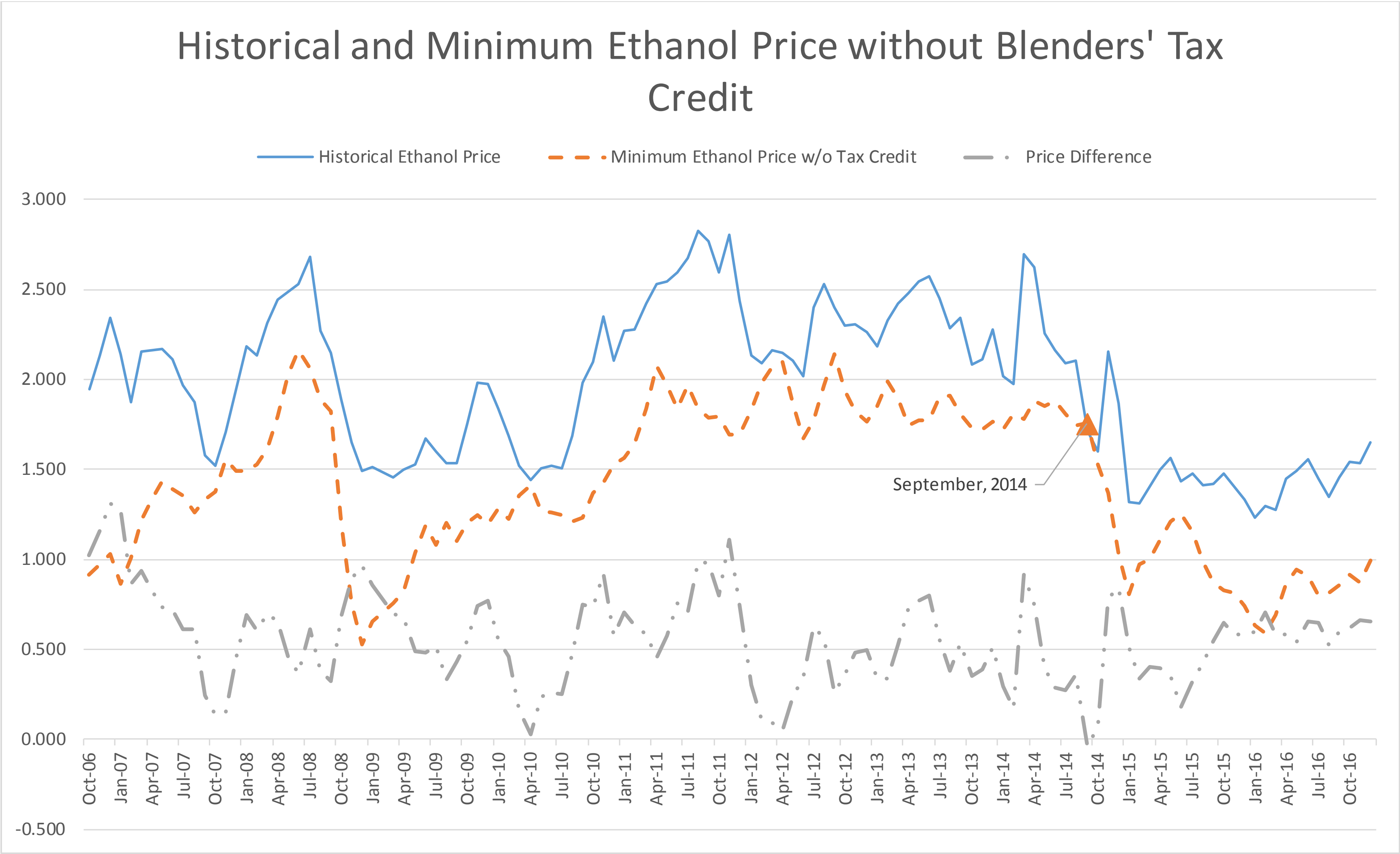

Figure 4.2.1 Historical and Minimum Ethanol Price without Blenders' Tax Credit

Source: Ethanol Price, Historical Ethanol Operating Margins, CARD, ISU

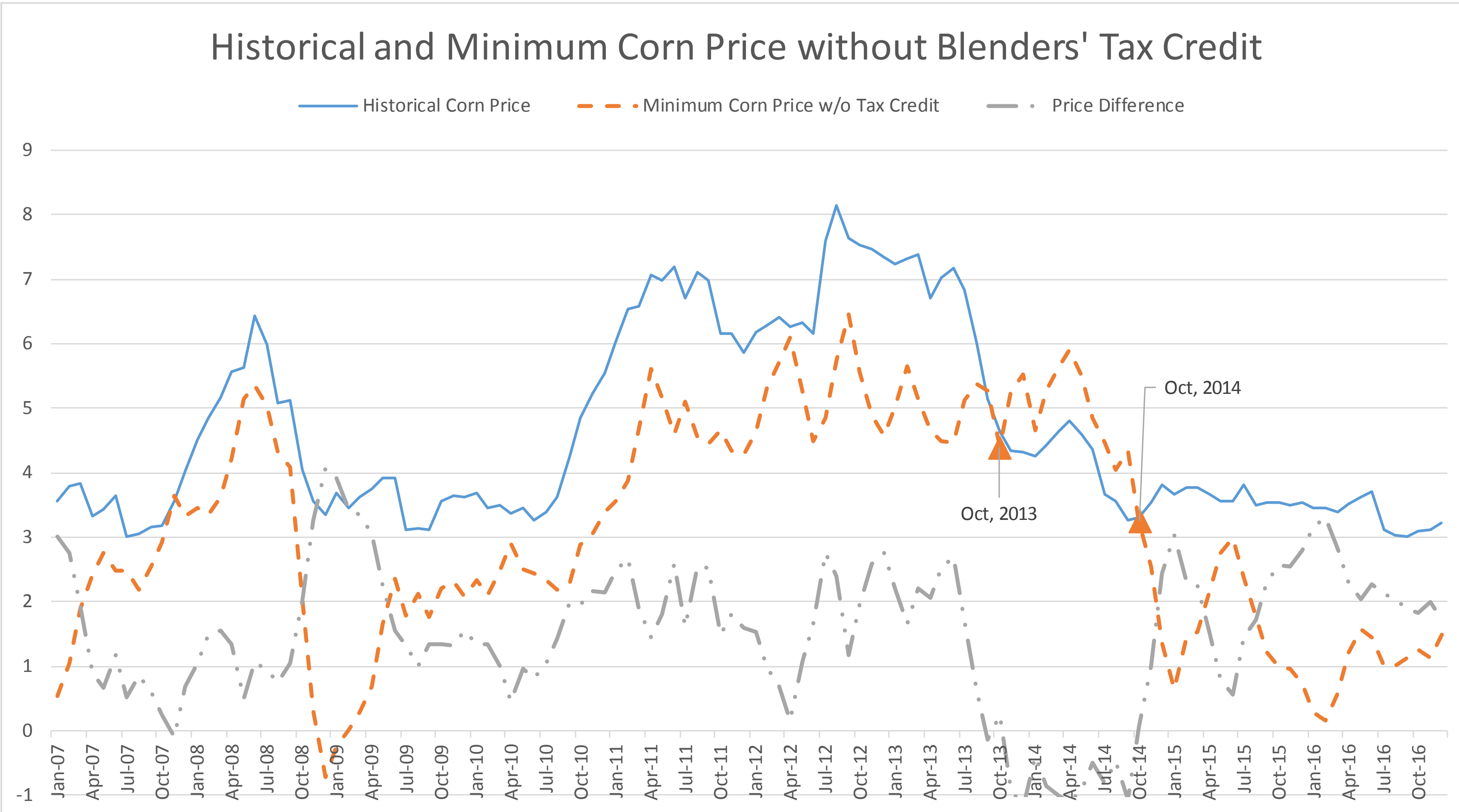

Figure 4.2.2 Historical and Minimum Corn Price without Blenders' Tax Credit

Source: Corn Price, Historical Ethanol Operating Margins, CARD, ISU

Between October 2013 and October 2014, the significant over-prediction has to do with multiple factors. Besides corn having a good harvesting year, a bad winter and the shortage of rail cars resulted in marketing constraints while ethanol price remained strong (de Gorter, Drabik, and Just, 2015). As the ethanol blend volume reached its cap of 15 billion in the next two years, ethanol prices also had a tendency to fall due to production decision beyond the blend goal, resulting in less ethanol production profit and lower minimum corn price. Overall, the removal of the blenders' tax credit should have led to lower corn price as ethanol production now takes up about one third of domestic corn production.

Figure 4.2.3 shows the minimum price of biodiesel. As we have mentioned in Chapter 3, the blend mandate regime is binding throughout our data period. As a result, retailers always sell biodiesel at a premium. In Figure 4.2.4, the minimum soybean price overall follows the real price and lies below it. The implication of the removal of the tax credit, however, is unclear at first. At one hand, the biodiesel industry claims the tax credit has very strong influence on production (biodiesel.org, 2017). If this is the case and assuming that U.S. does not acquire enough biodiesel through import to compensate for domestic production loss, historical biodiesel price would have been higher. On the other hand, even though domestic production will drop if the tax credit no longer exists, blenders may still acquire enough foreign import for the biodiesel market at the lower price. Based on what has happened in the history, the second scenario is more likely to happen though sudden increase in the price of biodiesel import has also happened in the past. Thus, we believe the removal of the tax credit is more likely to reduce the overall price of biodiesel during the period given that the international market can supply US with enough biodiesel to meet its annual blend goals. However, the price may also become more volatile if

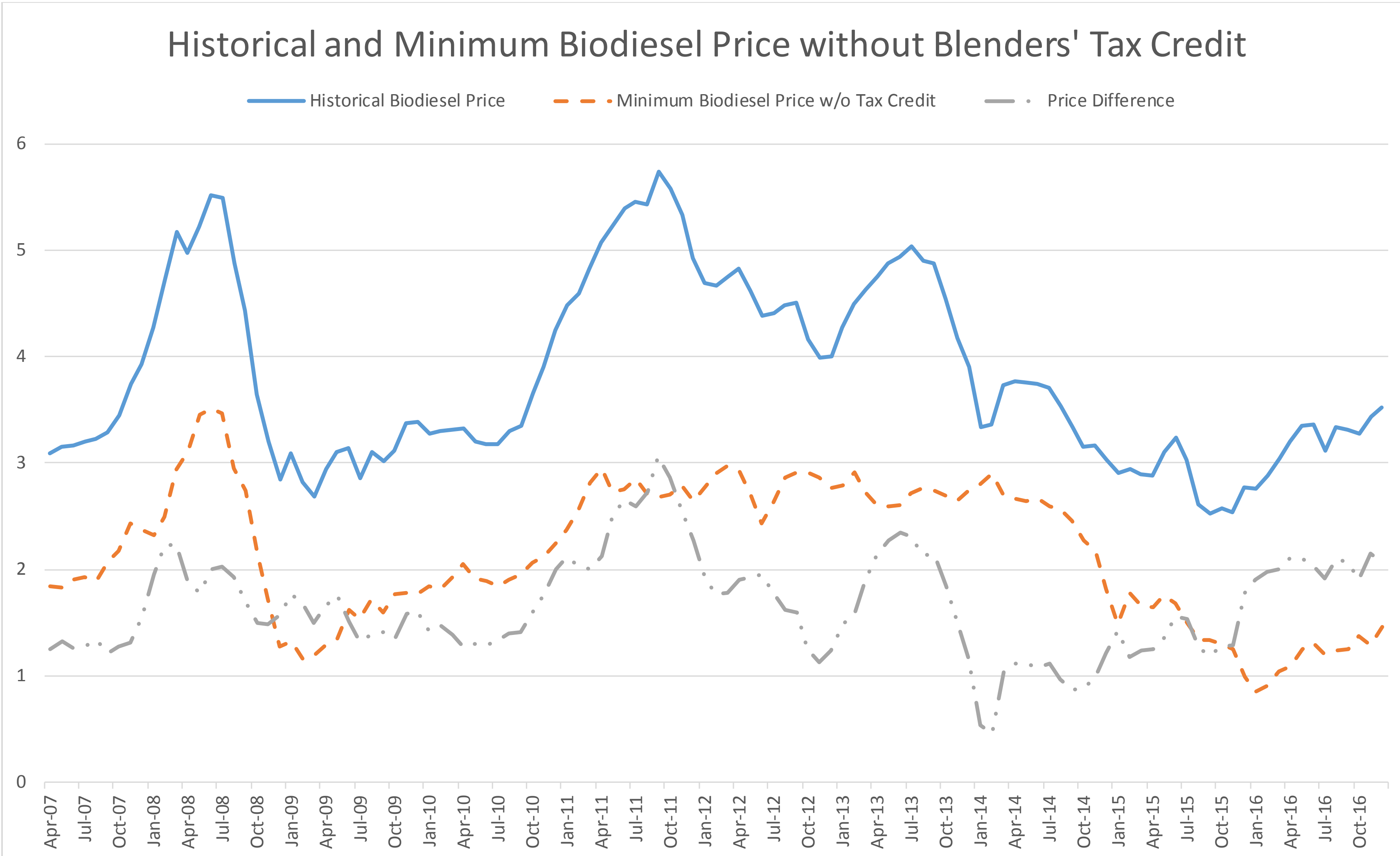

Figure 4.2.3 Historical and Minimum Biodiesel Price without Blenders' Tax Credit

Source: Biodiesel Price, Historical Biodiesel Operating Margins, CARD, ISU

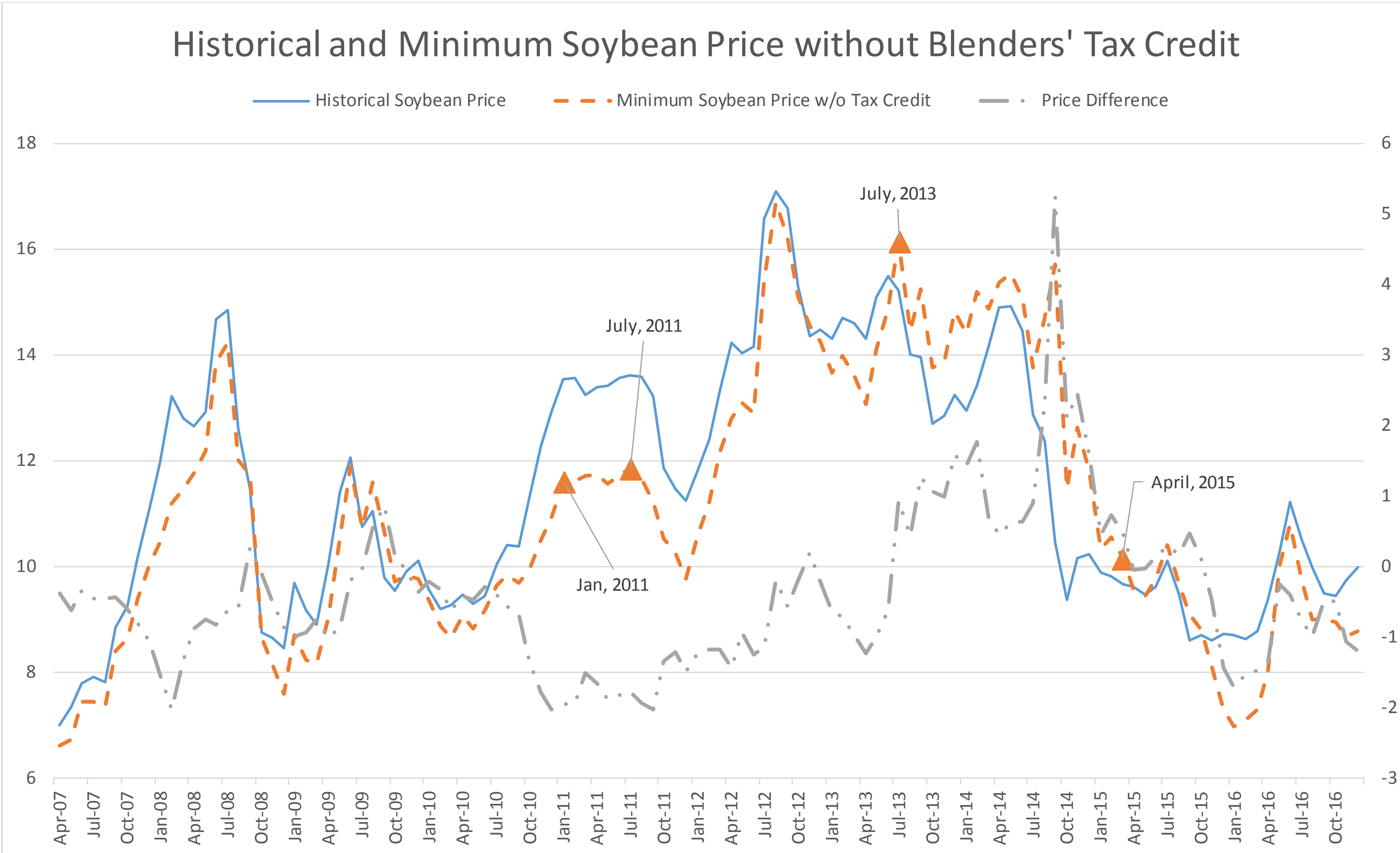

Figure 4.2.4 Historical Soybean and Minimum Soybean Price without Blenders' Tax Credit

Source: 48% Soybean Meal Truck Delivery Spot Price/Illinois (USD/short ton); USDA, Daily, Bloomberg

domestic industry fails to expand over time and international trade agreements change frequently between the US and its partners.

The price trend of soybean displays a different pattern. While soybean's minimum price is lower than the actual historical price most of the time, there are periods when the minimum price lies above the actual price, such as for the period between July, 2013 and April, 2015. One possible cause was the volatile production during the period in Figure 2.2.2. As production levels keep changing, soybean price follows. However, such a relationship would require a strong price link between the two commodities and the current domestic biodiesel production level is still low relative to the production growth in ethanol production in the past few years.

Table 4.2.1 Annual Production and Blend Goals

Year	Cellulosic Biofuel Goal	Cellulosic Biofuel Production	Biomass-Based Diesel Goal	Biodiesel Production	Advanced Biofuel Goal
2009	NA	NA	0.5	0.516	0.6
2010	0.1	0	0.65	0.343	0.95
2011	0.25	0	0.8	0.967	1.35
2012	0.5	0.000020	1.0	0.991	2.0
2013	1.0	0.000422	1 billion minimum	1.359	2.75
2014	1.75	0.033	1 billion minimum	1.279	3.75
2015	3	0.117	1 billion minimum	1.263	5.5
2016	4.25	0.171	1 billion minimum	1.556	7.25
2017	5.5	NA	1 billion minimum	NA	9.0
2018	7.0	NA	1 billion minimum	NA	11.0
2019	8.5	NA	1 billion minimum	NA	13.0
2020	10.5	NA	1 billion minimum	NA	15.0
2021	13.5	NA	1 billion minimum	NA	18.0
2022	16.0	NA	1 billion minimum	NA	21.0

Source: Program Overview for Renewable Fuel Standard Program, EPA/EIA Monthly Energy Review, Table 10.4/Public Data for the Renewable Fuel Standard, EPA

In the RFS, biodiesel falls below the biomass-based diesel category and can be used to fulfill the annual blend goal of advanced biofuel, which includes cellulosic biofuel, biodiesel, and sugarcane ethanol (EPA, 2017). As shown in Table 4.2.1, though biodiesel production has met its annual goals most of the time in the past few years, the volume blend goals for both cellulosic biofuel and advanced biofuel increase over years. Meanwhile, cellulosic biofuel production made significant gains in 2015 and is likely to expand at a faster pace with both technology and policy in place (Lane, 2016). Whether we will have more biodiesel production in the future that will create a tighter price link between biodiesel and soybean depends on the production of cellulosic biofuel and sugarcane ethanol and any future policy change for biodiesel production.

4.3 When There Is Tax Credit Throughout

In this simulation scenario, we investigate the implication of the continuation of the biofuel blenders' tax credit on the prices of biofuels and crops. In particular, we assume the 49.8 cents ethanol tax credit continued to exist after December 2011 for the rest of the period and the 1-dollar biodiesel tax credit was available in 2010, 2012, and 2015. Again, we do not study the change's influence on energy and crude oil as we assume their supplies are exogenous.

Figure 4.3.1 shows the simulated minimum price and historical price of ethanol. Compared to 4.2.1, the extension of the tax credit clearly raised the minimum price of ethanol. Depending on which regime is binding, historical ethanol price after December 2011 may have been higher or lower than this minimum price. However, based on what we have observed in the past and the assumption that blenders will bid up the price to fully take the blenders' tax credit, it is very likely that ethanol price would have increased as a result of the tax credit extension.

With the tax credit extension, minimum corn price was higher after January 2012. Compared to the price level in the same period in Figure 4.2.2, the minimum corn price was above the historical corn price in Figure 4.3.2 during the same period most of the time even after taking into consideration of the period between October 2013 and October 2014. With ethanol

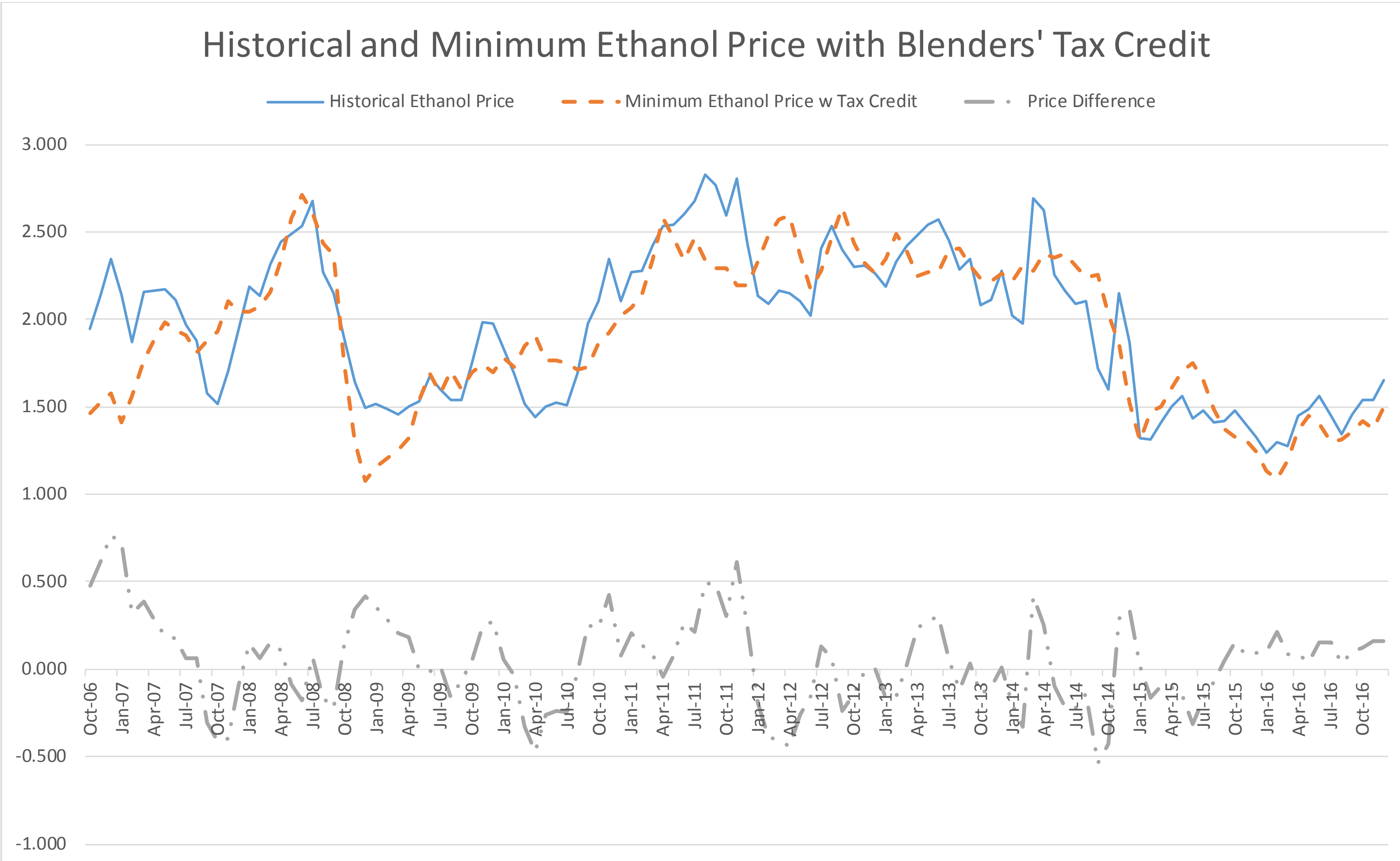

Figure 4.3.1 Historical and Minimum Ethanol Price with Blenders' Tax Credit

Source: Ethanol Price, Historical Ethanol Operating Margins, CARD, ISU

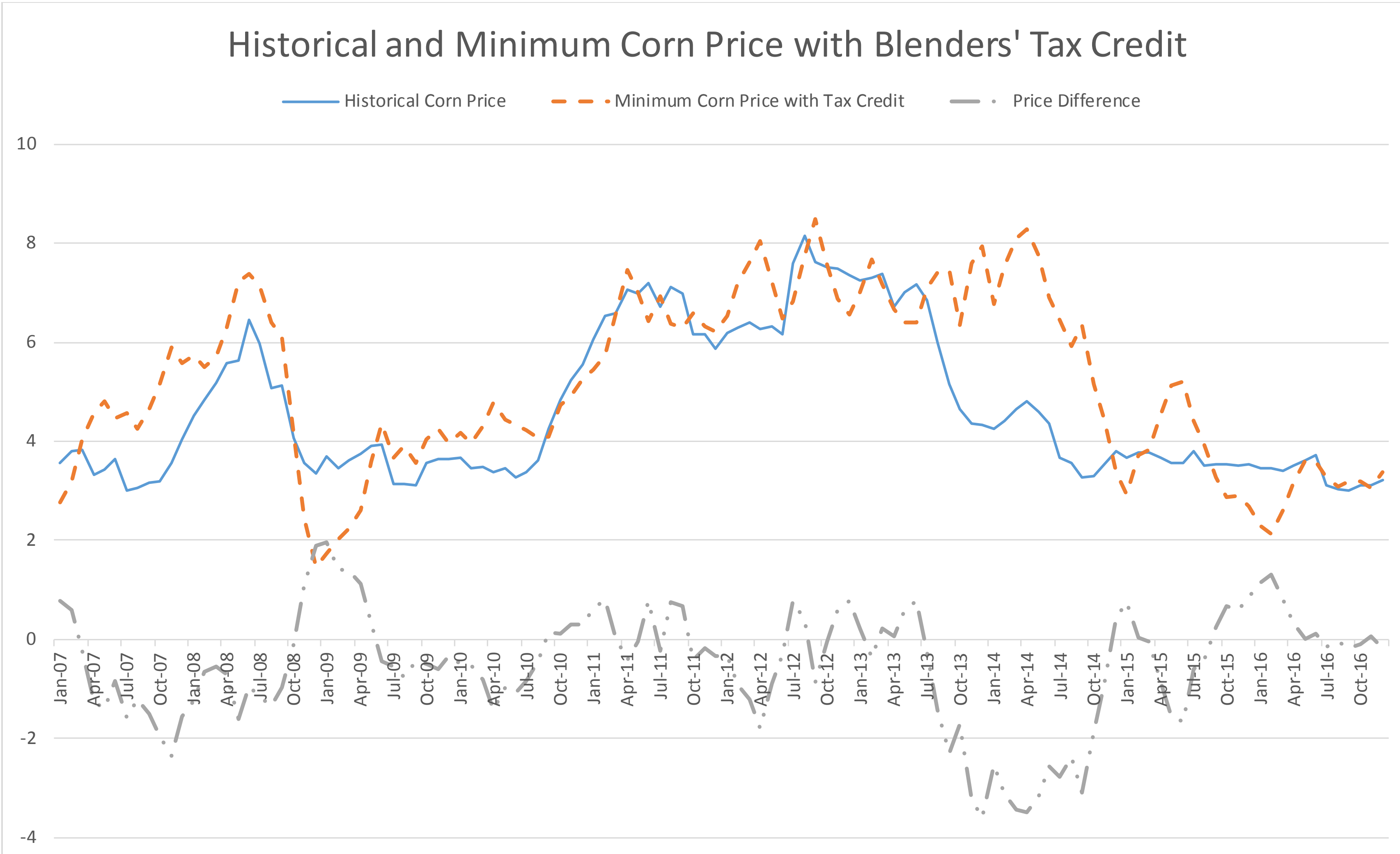

Figure 4.3.2 Historical and Minimum Corn Price with Blenders' Tax Credit

Source: Corn Price, Historical Ethanol Operating Margins, CARD, ISU

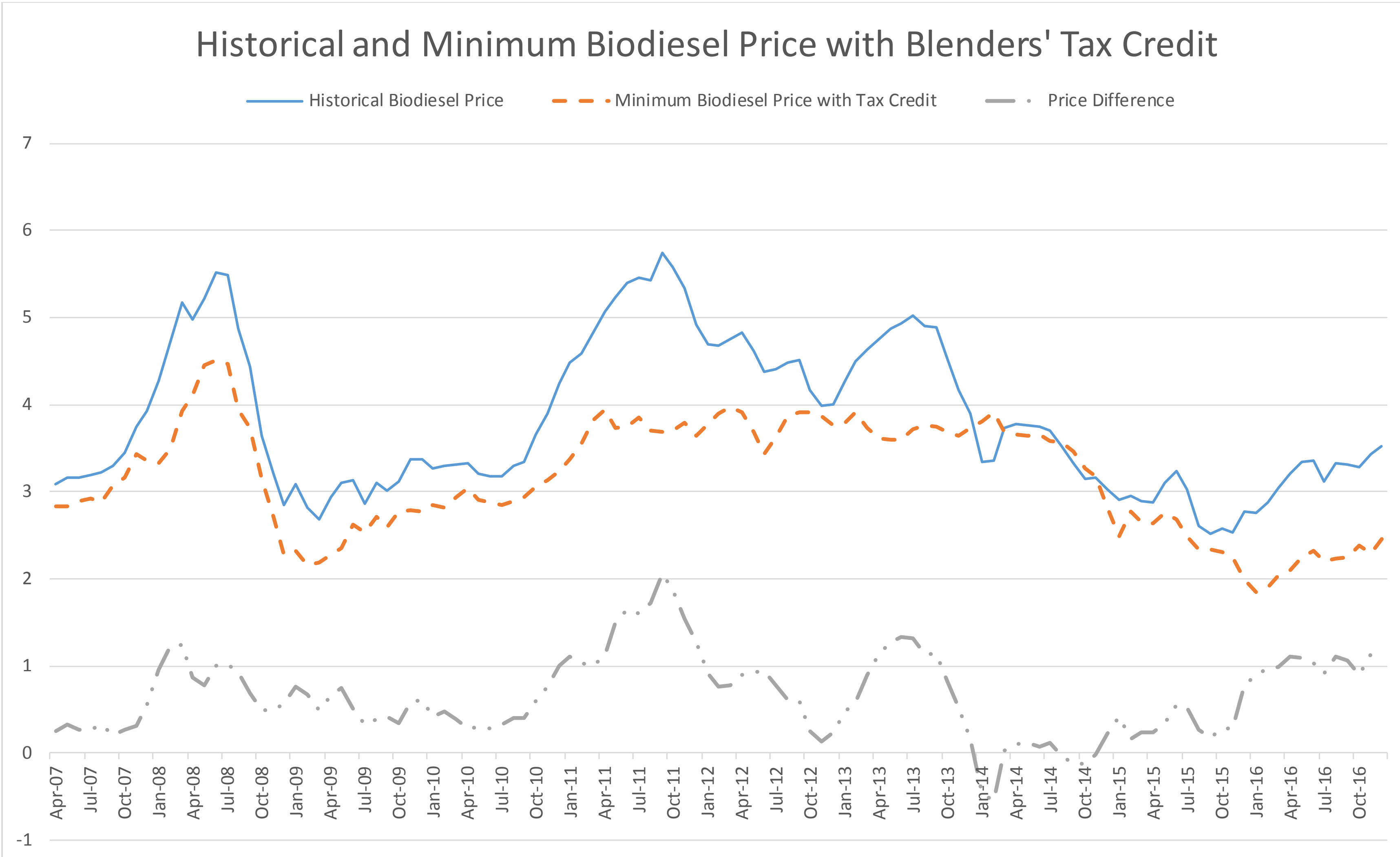

Figure 4.3.3 Historical and Minimum Biodiesel Price with Blenders' Tax Credit

Source: Biodiesel Price, Historical Biodiesel Operating Margins, CARD, ISU

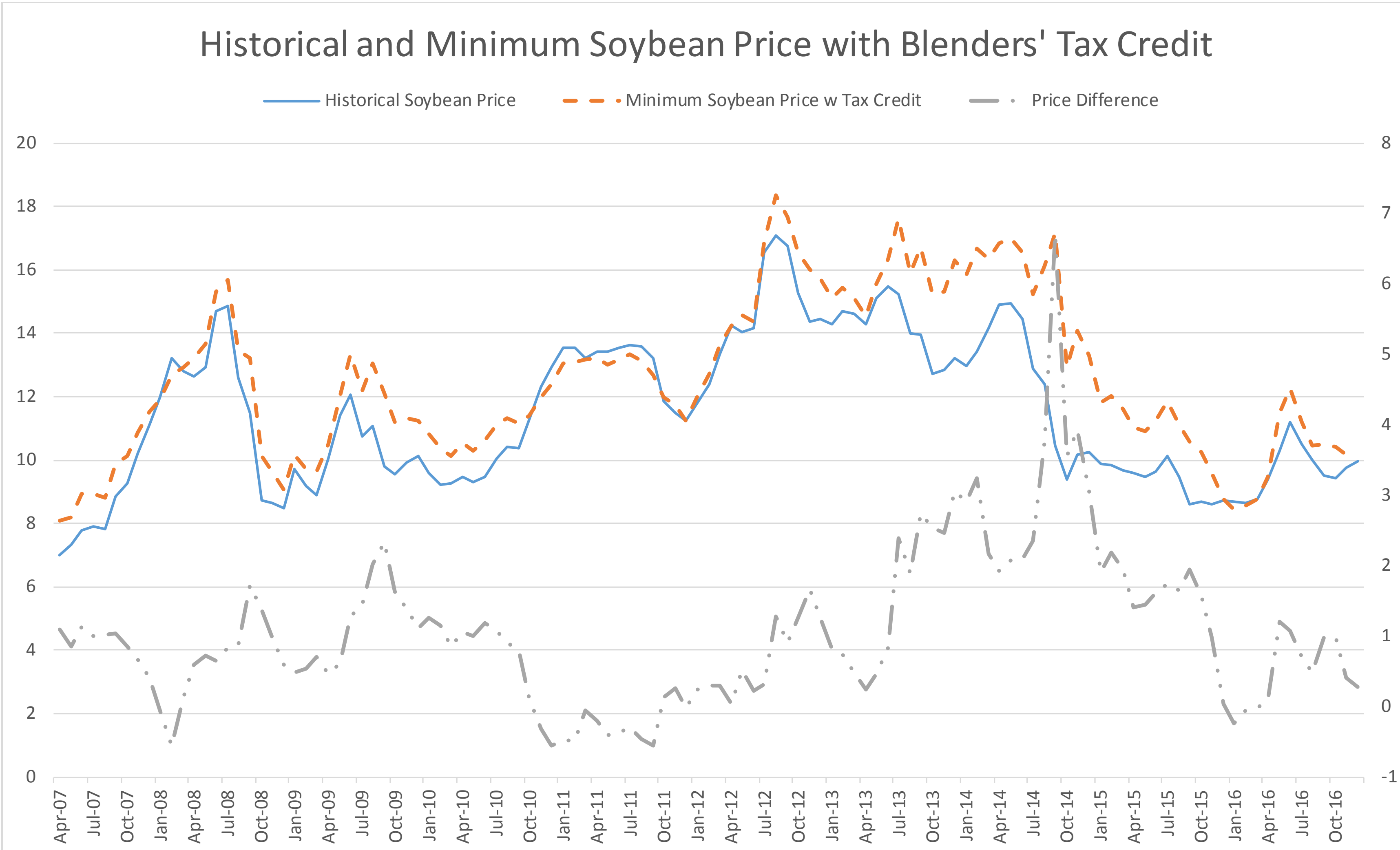

Figure 4.3.4 Historical Soybean and Minimum Soybean Price with Blenders' Tax Credit

Source: 48% Soybean Meal Truck Delivery Spot Price/Illinois (USD/short ton); USDA, Daily, Bloomberg

production capacity stabilizing and the capping of the blend goals of the RFS, the corn price was very likely to increase due to the price premium in the biofuel industry.

When biodiesel receives a blenders' tax credit throughout the period, the overall price premium of biodiesel decreased in Figure 4.3.3. In addition, the historical soybean price was below the minimum price during certain data periods. This suggests the two regimes may start to exist for the price relationship between biodiesel if the industry continues to receive the support and expand. This may eventually lead to a more competitive biodiesel market like that of ethanol.

Lastly, if the biodiesel market matured, the overall soybean price would have been higher than the actual price in Figure 4.3.4. This price pattern is similar to the results in Figure 3.3.2.2 using the actual biodiesel price. However, depending on what the EPA does in the future for the annual blend goals of biodiesel, the tight price link between soybean and biodiesel that will induce such price transmission may take a few years to develop.

CHAPTER 5

CONCLUSION

The motivation of this thesis is to study the price links between energy and crop since the beginning of the mass production of biofuels in the United States back in 2006 using a model that considers both biofuel policies and economic fundamentals. Despite the large amount of attention researchers have given to the study of the economics of biofuels, little work has included an individualized set of economic analysis framework for this policy-induced market whose behaviors differ from those of normal supply and demand frameworks. Building upon the theoretical framework of an economic model that specifically deals with biofuels, we explored the price relationships between energy and crop commodities and the sources of price divergence, tested the soundness of the economic model, simulated three market and policy scenarios to study market impact, and provided possible explanations when the predictions of these models deviate from what happened in reality.

Overall, we believe input and output relationships and biofuel policies have created price links between the following commodity pairs: crude oil-gasoline, gasoline-ethanol, ethanol-corn, crude oil-diesel, diesel-biodiesel, and biodiesel-soybean oil. Price links exist between gasoline and diesel and crude oil, with crude oil being the main input for the two energy products. For the rest of the price links, however, due to the existence of two states of nature (the tax credit regime and the mandate premium regime) stemmed from the requirements of the Renewable Fuel Standard, the links between fuel-biofuel and biofuel-crop can become delinked at times.

We tested hypotheses on binding regimes between commodity pairs. Based on the correlations between fuels and biofuels, diesel and biodiesel does not display the high mandate premium-low correlation pattern as predicted by the model while gasoline and ethanol shows the opposite result. Moreover, while the price pattern of the minimum ethanol price and real ethanol price shows the existence of the two regimes, the comparison between the minimum corn price and the actual corn price suggests the mandate premium regime is binding throughout the data period. Lastly, both the minimum soybean and biodiesel prices correspond with each other in terms of the mandate premium regime being binding during the whole time.

We then used the estimated economic model for three simulations: (1) what if the price of a barrel of crude oil stayed at $110 beginning January, 2008; (2) what if biofuel blenders' tax credit did not exist from the beginning; and (3) what if biofuel blenders' tax credit continued to exist throughout the data period. In the first scenario, when crude oil stays at 110 per barrel, ethanol prices increase due to the higher gasoline prices. This in turn would result in higher corn prices. The same pattern holds for soybeans. Higher crude oil prices lead to higher diesel and biodiesel prices that would push up soybean prices. In the second scenario, the removal of the blenders' tax credit will result in overall lower ethanol and corn prices. However, the minimum corn prices without the tax credit does not always have to be lower than the actual corn prices due to factors like marketing constraints, international trade, and yearly production. Biodiesel prices have a slightly different story due to the continued expansion in domestic production and imports still capturing a significant market share may push biodiesel prices in different directions. However, the removal of the tax credit should reduce the overall price of biodiesel and soybean price will also decrease accordingly. Lastly, in the third scenario, the extension of the tax credit will increase ethanol and corn prices even after taking into considerations of ethanol reaching the RFS blend cap in 2016 and the good harvest of 2014. For biodiesel and soybeans, the extension increase prices but as the industry matures, we may start to see the tax credit regime to step in.

Despite the explanations we provide to account for some of the differences between model's prediction and reality whenever possible, there still remains divergences unaccounted for and sometimes we cannot adjust price variables in response to other changes in the market to reflect a policy's impacts. For example, we cannot explain why we obtained opposite results when we tested the hypothesis of high mandate premium leading to low gasoline and ethanol price correlation. Also, when we set crude oil to be 110 dollars per barrel, the crushing of more soybeans to produce biodiesel due to a higher diesel price will certainly lead to more soybean meal being available in the market at a lower price. However, the limitation of our model does not allow for a price adjustment and hence will certainly result in prediction errors in the trend of soybean price. To solve these issues, future research should develop structural models with policy-invariant parameters to disentangle the price links between energy and crop commodities.

The beginning of the mass production of biofuel in the United States has great implications for the production patterns and price trends in the energy and crop markets. The intricate, nuanced, and evolving biofuel policies render the study of the interaction between the two markets challenging. We leave future work that shed more light on the open questions here.

References

Baffes, John. 2007. “Oil Spills On Other Commodities,” Policy Research Working Papers, , November. doi:10.1596/1813-9450-4333.

Balcombe, Kelvin, and George Rapsomanikis. 2008. “Bayesian Estimation and Selection of Nonlinear Vector Error Correction Models: The Case of the Sugar-Ethanol-Oil Nexus in Brazil.” *American Journal of Agricultural Economics* 90 (3): 658–68.

Barnett, Vic, and Toby Lewis. 1984. *Outliers in Statistical Data*. 2nd Edition. Wiley Series in Probability and Mathematical Statistics. Wiley.

Buhl, Larry. 2016. “Why There Could Be More Blasts Like 2015 ExxonMobil Torrance Oil Refinery Explosion, Putting Millions At Risk.” *DeSmogBlog*. June 1. https://www.desmogblog.com/2016/05/31/why-there-could-be-more-blasts-2015-exxonmobil-torrance-oil-refinery-explosion-putting-millions-risk.

“CRS-RFS-Overview-Issues.pdf.” 2017. Accessed May 5. https://www.ifdaonline.org/IFDA/media/IFDA/GR/CRS-RFS-Overview-Issues.pdf.

Department of State. 2017. “Milestones: 1969–1976 - Office of the Historian.” Accessed March 15. https://history.state.gov/milestones/1969-1976/oil-embargo.

EIA. 2017a. “Biofuels: Ethanol and Biodiesel - Energy Explained, Your Guide To Understanding Energy - Energy Information Administration.” https://www.eia.gov/energyexplained/index.cfm/data/index.cfm?page=biofuel_home.

———. 2017b. “U.S. Energy Facts - Energy Explained.” https://www.eia.gov/energyexplained/?page=us_energy_home#tab1.

———. 2017c. “U.S. Field Production of Crude Oil (Thousand Barrels per Day).” https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=MCRFPUS2&f=A.

———. 2017a. “Gasoline and Diesel Fuel Update - Energy Information Administration.” *U.S. Energy Information Administration*. Accessed March 15. https://www.eia.gov/petroleum/gasdiesel/.

———. 2017b. “Refining Crude Oil - Energy Explained, Your Guide To Understanding Energy - Energy Information Administration.” *U.S. Energy Information Administration*. Accessed March 15. https://www.eia.gov/Energyexplained/index.cfm?page=oil_refining.

———. 2017c. “U.S. Refinery Yield.” *U.S. Energy Information Administration*. Accessed March 15. https://www.eia.gov/dnav/pet/PET_PNP_PCT_DC_NUS_PCT_A.htm.

ERS, USDA. 2017a. “Crop Production Annual Summary 2016.” http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1047.

———. 2017b. “Feed Outlook Jan 17, 2017.” http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1273.

———. 2017. “USDA ERS - Commodity Costs and Returns.” Accessed April 15. https://www.ers.usda.gov/data-products/commodity-costs-and-returns/commodity-costs-and-returns/#Recent Costs and Returns: Soybeans.

“Ethanol-Industry-Outlook-2016.pdf.” 2017. Accessed May 5. http://www.ethanolrfa.org/wp-content/uploads/2016/02/Ethanol-Industry-Outlook-2016.pdf.

Galloway, Richard. 2016. “Domestic Industry Crush Lower Than Last Year.” *Qualisoy*. May 4. http://www.qualisoy.com/resources/market-updates/market-updates/2016/05/04/domestic-industry-crush-lower-than-last-year.

Gorter, Harry de, Dusan Drabik, and David Just. n.d. *The Economics of Biofuel Policies Impacts on Price Volatility in Grain and Oilseed Markets*. One. Palgrave Studies in Agricultural Economics and Food Policy. Palgrave Macmillan.

Gorter, Harry de, and David R. Just. 2009. “The Economics of a Blend Mandate for Biofuels.” *American Journal of Agricultural Economics* 91 (3): 738–50.

Haniotis, Tassos Baffes, John. 2010. “Placing The 2006/08 Commodity Price Boom Into Perspective,” Policy Research Working Papers, , August. doi:10.1596/1813-9450-5371.

Headey, Derek, and Shenggen Fan. 2008. “Anatomy of a Crisis: The Causes and Consequences of Surging Food Prices.” *Agricultural Economics* 39 (s1): 375–91.

Janick, Jules. 2008. “Lecture 32 Agricultural Scientific Revolution: Mechanical.” https://www.hort.purdue.edu/newcrop/Hort_306/text/lec32.pdf.

Knittel, Christopher R., and Aaron Smith. 2015. “Ethanol Production and Gasoline Prices: A Spurious Correlation.” *The Energy Journal* 36 (1). doi:10.5547/01956574.36.1.4.

Lane, Bruce. 2000. “Feeding Whole Soybeans to Cattle.” December. http://agebb.missouri.edu/mgt/lane.htm.

Lane, Jim. 2016. “Cellulosic Ethanol, What Happened, What’s Happening? : Biofuels Digest.” *BiofuelsDigest*. August 1. http://www.biofuelsdigest.com/bdigest/2016/08/01/cellulosic-ethanol-what-happened-whats-happening/.

Minerals Management Service. 2005. “Hurricane Katrina/Hurricane Rita Evacuation and Production Shut-In Statistics Report as of Friday, September 30, 2005.” #3368. https://www.bsee.gov/sites/bsee.gov/files/reports/reports/press0930.pdf.

Nazlioglu, Saban, and Ugur Soytas. 2012. “Oil Price, Agricultural Commodity Prices, and the Dollar: A Panel Cointegration and Causality Analysis.” *Energy Economics* 34 (4): 1098–1104. doi:10.1016/j.eneco.2011.09.008.

Nebraska Government. 2017. “Ethanol Production Capacity by State.” http://www.neo.ne.gov/statshtml/121/2015/121_201510.htm.

Oynes, Chris. 2006. “Oil, Gas, and Society: Hurricane Preparations after Katrina.” Baker Institute at Rice University, August 22. https://www.bsee.gov/sites/bsee.gov/files/safety-alerts/preparation/baker-inst-rice-univ.pdf.

Parker, Mario. 2015. “There Goes the `Blend Wall’ Keeping More Ethanol Out of Gasoline.” *Bloomberg.com*. November 30. https://www.bloomberg.com/news/articles/2015-12-01/there-goes-the-blend-wall-keeping-more-ethanol-out-of-gasoline.

Renewable Fuel Association. 2015. “E15.” *Renewable Fuels Association*. June 12. http://www.ethanolrfa.org/resources/blends/e15/.

Roberts, Michael J., and Wolfram Schlenker. 2013. “Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate.” *The American Economic Review; Nashville* 103 (6): 2265–95. doi:http://dx.doi.org.proxy.library.cornell.edu/10.1257/aer.103.6.2265.

Rosegrant, Mark W., Tingju Zhu, Siwa Msangi, and Timothy Sulser. 2008. “Global Scenarios for Biofuels: Impacts and Implications.” *Review of Agricultural Economics* 30 (3): 495–505.

Schnepf, Randy. 2010. “Agriculture-Based Biofuels: Overview and Emerging Issues.” Congressional Research Service. http://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1016&context=crsdocs.

Schnepf, Randy, and Brent Yacobucci. 2013. “Renewable Fuel Standard (RFS): Overview and Issues.” Congressional Research Service. https://www.ifdaonline.org/IFDA/media/IFDA/GR/CRS-RFS-Overview-Issues.pdf.

Serra, Teresa, and David Zilberman. 2013. “Biofuel-Related Price Transmission Literature: A Review.” *Energy Economics* 37 (May): 141–51. doi:10.1016/j.eneco.2013.02.014.

Serra, Teresa, David Zilberman, and José Gil. 2011. “Price Volatility in Ethanol Markets.” *European Review of Agricultural Economics* 38 (2): 259–80. doi:10.1093/erae/jbq046.

Serra, Teresa, David Zilberman, José M. Gil, and Barry K. Goodwin. 2011. “Nonlinearities in the U.S. Corn-Ethanol-Oil-Gasoline Price System.” *Agricultural Economics* 42 (1): 35–45. doi:10.1111/j.1574-0862.2010.00464.x.

Squillace, Paul, Daryll Pope, and Curtis Price. 1995. “Occurrence of the Gasoline Additive MTBE in Shallow Ground Water in Urban and Agricultural Areas.” https://sd.water.usgs.gov/nawqa/pubs/factsheet/fs114.95/fact.pdf.

“Tax Incentive Action Page - Biodiesel.org.” 2017. *Biodiesel.org*. http://biodiesel.org/policy/fueling-action-center/tax-incentive-action-page.

The British Medical Journal. 1928. “Tetra-Ethyl Lead as An Addition to Petrol,” March, 866.

Tyner, Wallace E. 2010. “The Integration of Energy and Agricultural Markets.” *Agricultural Economics* 41 (November): 193–201. doi:10.1111/j.1574-0862.2010.00500.x.

US EPA, OAR. 2017a. “Clean Air Act Requirements and History.” Overviews and Factsheets. https://www.epa.gov/clean-air-act-overview/clean-air-act-requirements-and-history.

———. 2017b. “Program Overview for Renewable Fuel Standard Program.” Overviews and Factsheets. https://www.epa.gov/renewable-fuel-standard-program/program-overview-renewable-fuel-standard-program.

———. 2017c. “Public Data for the Renewable Fuel Standard.” Data and Tools. https://www.epa.gov/fuels-registration-reporting-and-compliance-help/public-data-renewable-fuel-standard.

USDA. 2017. “FAS Grain: World Markets and Trade.”

“USDA Crop Production Historical Track Records April 2017.” 2017. Accessed May 9.

http://usda.mannlib.cornell.edu/usda/current/htrcp/htrcp-04-13-2017.pdf.

Zilberman, David, Gal Hochman, Deepak Rajagopal, Steve Sexton, and Govinda Timilsina. 2013. “The Impact of Biofuels on Commodity Food Prices: Assessment of Findings.” *American Journal of Agricultural Economics* 95 (2): 275–81. doi:10.1093/ajae/aas037.